Achieving stringent climate targets: An analysis of the role of transport and variable renewable energies using energy-economy-climate models

vorgelegt von
Diplom-Physiker
Robert Carl Pietzcker
geboren in Bonn

von der Fakultät VI – Planen Bauen Umwelt
der Technischen Universität Berlin
zur Erlangung des akademischen Grades
Doktor der Wirtschaftswissenschaften
Dr. rer. oec.

genehmigte Dissertation

Promotionsausschuss:

Vorsitzender:	Prof. Dr. Volkmar Hartje
Gutachter:	Prof. Dr. Ottmar Edenhofer
Gutachter:	Prof. Dr. Christian von Hirschhausen

Tag der wissenschaftlichen Aussprache: 21.10.2014

Berlin 2015
D 83

Contents

Abstract **7**

Zusammenfassung **9**

Nomenclature **11**

1 Introduction **13**
- 1.1 Climate change 14
- 1.2 Economics of climate change mitigation 15
- 1.3 Integrated Assessment Models 19
- 1.4 Decarbonizing the energy system 26
- 1.5 Thesis objective and outline 32
- References 35

2 Asia's role in mitigating climate change **57**
- 2.1 Introduction 59
- 2.2 Model and scenario setup 60
- 2.3 Secondary energy based mitigation shares 61
- 2.4 Economic mitigation potential of technologies 62
- 2.5 Climate change mitigation in Asia 65
- 2.6 Discussion: methodological issues 68
- 2.7 Summary and conclusion 68
- 2.8 References 70
- 2.9 Supplementary Material 72

3 The role of renewable energy in climate stabilization **83**
- 3.1 Introduction 86
- 3.2 RE deployment pathways 87

3.3 The relevance of RES for mitigation 90
3.4 Determinants of wind and solar power deployment 94
3.5 Conclusions 98
3.6 References 99
3.7 Supplementary Material 100

4 Using the sun to decarbonize the power sector 111
4.1 Introduction 114
4.2 Study design 114
4.3 System integration costs 116
4.4 Solar power technology investment costs 119
4.5 Solar resource potential 120
4.6 Scenario Results 122
4.7 Summary and conclusions 126
4.8 Bibliography 127
4.9 Supplementary Information 130

5 Long-term transport energy demand and climate policy 147
5.1 Introduction 149
5.2 Methodology 150
5.3 General scenario results 154
5.4 Analysis and discussion of mitigation pathways 156
5.5 Summary and conclusion 159
5.6 References 161

6 Economic mitigation challenges 163
6.1 Introduction 165
6.2 Methods 166
6.3 Results 167
6.4 Discussion and conclusions 170
6.5 References 171
6.6 Supplementary Material 173

7 Synthesis and Outlook 199
7.1 Summary of results 199
7.2 Discussion of results and policy implications 203

7.3 Discussion of methods 208
7.4 Suggestions for future research 211
References 213

Statement of Contributions 225

Tools and Resources 227

Acknowledgements 229

Abstract

Anthropogenic climate change is threatening the welfare of mankind. Accordingly, policy makers have repeatedly stated the goal of slowing climate change and limiting the increase of global mean temperature to less than 2°C above pre-industrial times (the so-called "two degree target"). Stabilizing the temperature requires drastic reductions of greenhouse gas (GHG) emissions to nearly zero. As the global system of energy supply currently relies on fossil fuels, reducing GHG emissions can only be achieved through a full-scale transformation of the energy system. There are many possible paths to realize such a decarbonization, resulting in a variety of distinct energy-economy systems. Different transformation paths require different technologies and system changes, and will result in different socio-economic and environmental impacts.

This thesis investigates the economic requirements and implications of different scenarios that achieve stringent climate mitigation targets[1]. It starts with the analysis of characteristic decarbonization patterns and identifies two particularly relevant aspects of mitigation scenarios: deployment of variable renewable energies (VRE) and decarbonization of the transport sector. To investigate the role of renewable energies, we performed both a comparative study across seventeen integrated assessment models (IAMs) as well as a detailed deep-dive with the IAM REMIND. For the transport sector, we undertook a comparative study of five IAMs. Finally, we turned towards one of the most relevant questions for policy makers and analyzed the trade-off between the stringency of a climate target and its economic requirements and implications. All analyses are based on the improvement, application, comparison, and discussion of large-scale IAMs.

We started by developing the novel "mitigation share" metric and applying it to scenarios produced with REMIND. This metric allowed us to identify the relevance of specific technology groups for mitigation and to improve our understanding of the decarbonization patterns of different energy subsectors. It turned out that the power sector is decarbonized first and reaches lowest emissions, while the transport sector is slowest to decarbonize. For the power sector, non-biomass renewable energies contribute most to emission reductions, while the transport sector strongly relies on liquid fuels and therefore requires biomass in combination with carbon capture and sequestration (CCS) to reduce emissions.

The subsequent comparison of seventeen IAMs used by different research groups worldwide generally confirms the findings from the previous analysis: For most models, the deployment of renewable energy sources increases substantially with the stringency of climate policy. In most of the low stabilization scenarios that have a high likelihood of achieving the 2°C target, renewable energy becomes the dominant source of electricity. Furthermore, the models with high renewable shares also show particularly high contributions from the VRE wind and solar. At the same time, the model comparison reveals large differences between actual technology deployment levels in the different models.

[1] "Stringent climate mitigation target" and "low stabilization scenario" in this thesis denote scenarios where the increase of global mean temperature is limited to 1.5–2.5°C above pre-industrial times.

An in-depth investigation of the solar power technologies photovoltaics (PV) and concentrating solar power (CSP) in REMIND confirms the dominant role of these variable renewable energies for the decarbonization of the power sector. Recent cost reductions have brought PV to cost-competitiveness in regions with high midday electricity demand and high solar irradiance. The representation of system integration costs in REMIND is found to have significant impact on the competition between PV and CSP in the model: the low integration requirements of CSP equipped with thermal storage and hydrogen cofiring make CSP competitive at high shares of variable renewable energies, which leads to substantial deployment of both PV and CSP in low stabilization scenarios.

A cross-model study of transport sector decarbonization reveals a number of different decarbonization routes, as well as the need for future model improvement to ensure that all decarbonization options along the chain of causality are well represented. Our research confirms the earlier finding that the transport sector is not very reactive to intermediate carbon price levels: Until 2050, transport decarbonization lags 10–30 years behind the decarbonization of other sectors, and liquid fuels dominate the transport sector. In the long term, however, transportation does not seem to be an insurmountable barrier to stringent climate targets: As the price signals on CO_2 increase further, transport emissions can be reduced substantially – if either hydrogen fuel cells or electromobility open a route to low-carbon energy carriers, or second generation biofuels (possibly in combination with CCS) allow the use of liquid-based transport modes with low emissions.

The last study takes up the fundamental question of this thesis and analyses the trade-off between the stringency of a climate target and the resulting techno-economic requirements and costs. We find that transforming the global energy-economy system to keep a two-thirds likelihood of limiting global warming to below 2°C is achievable at moderate economic implications. This result is contingent on the near-term implementation of stringent global climate policies and full availability of several technologies that are still in the demonstration phase. Delaying stringent policies and extending the current period of fragmented and weak action will substantially increase mitigation costs, such that stringent climate targets might be pushed out of reach. Should the current weak climate policies be extended until 2030, the transitional mitigation costs for keeping the 2°C target would increase three-fold compared to a world in which global cooperative action is decided on in 2015 and where first deep emission reductions are achieved in 2020. In case of technology limitations, the urgency of reaching a global climate agreement is even higher.

In this thesis, we performed a comprehensive analysis of stringent mitigation scenarios and their economic implications, with a special focus on VRE deployment and transport decarbonization. Based on extensive modeling work and global cross-model analyses, this thesis provides crucial insights and identifies strategies for achieving stringent mitigation targets.

Zusammenfassung

Der anthropogene Klimawandel gefährdet das Wohlergehen der Menschheit. Aus diesem Grund haben Politiker wiederholt das Ziel formuliert, den Klimawandel zu verlangsamen und die Erhöhung der mittleren globalen Temperatur auf weniger als 2°C über dem vorindustriellen Wert zu begrenzen. Um den Temperaturanstieg zu stoppen, müssen die globalen Treibhausgasemissionen nahezu vollständig vermieden werden. Da das heutige globale System zur Energienutzung auf fossilen Rohstoffen beruht, erfordert die Reduktion von Treibhausgasemissionen eine umfangreiche Umgestaltung unseres Energiesystems. Es gibt eine Reihe unterschiedlicher Strategien, um eine solche Dekarbonisierung zu erreichen, und eine Vielzahl von möglichen Energie- und Wirtschaftssystemen, die mit niedrigen Treibhausgasemissionen einhergehen. Diese Strategien unterscheiden sich sowohl in ihren Technologien als auch in der jeweiligen Umgestaltung der Energiesysteme und bringen insofern verschiedene Umwelt- und sozio-ökonomischen Folgen mit sich.

Diese Arbeit erforscht die ökonomischen Anforderungen und Folgen von ambitionierten Klimaschutzzielen[2]. Sie beginnt mit einer allgemeinen Analyse der charakteristischen Dekarbonisierungsmuster des globalen Energiesystems. Diese identifiziert zwei besonders relevante Aspekte von Klimaschutzszenarien: die Nutzung von variablen erneuerbaren Energien (VRE) und die Dekarbonisierung des Verkehrssektors. Für die Analyse der VRE führen wir eine Vergleichsstudie über 17 Integrated Assessment Models (IAM) durch, gefolgt von einer Detailstudie mit dem IAM REMIND. Für den Verkehrssektor vergleichen und diskutieren wir Aufbau und Ergebnisse von fünf IAMs. Abschließend wenden wir uns der für die Politik fundamentalen Frage zu, wie sich die Strenge eines Klimaschutzziels auf seine ökonomischen Folgen auswirkt. Die Arbeit beruht auf der Verbesserung, der Anwendung sowie dem Vergleich von IAMs.

In einem ersten Schritt haben wir eine Metrik entwickelt, die es erlaubt, die Bedeutung einzelner Technologiegruppen für die Emissionsvermeidung zu identifizieren. Dies ermöglicht ein besseres Verständnis der Dekarbonisierungsmuster, die die jeweiligen Energiesektoren zeigen. Unsere Analyse ergibt, dass zunächst der Stromsektor dekarbonisiert wird und die niedrigsten Emissionen erreicht, wohingegen sich die Emissionen im Verkehrssektor am langsamsten verringern lassen. Im Stromsektor tragen die erneuerbaren Energien Wind, Solar und Wasserkraft am meisten zur Emissionsreduktion bei. Im Gegensatz dazu benötigt der Verkehrssektor in großem Maße Flüssigtreibstoffe, deren Emissionen hauptsächlich durch Biomasseverflüssigung in Verbindung mit Kohlenstoffabtrennung und -speicherung (CCS) reduziert werden können.

Der anschließende Vergleich einer Reihe von IAMs, welche von internationalen Forschungsgruppen verwendet werden, bestätigt diese Erkenntnisse größtenteils: Bei den meisten Modellen steigt die Nutzung von erneuerbaren Energien substantiell mit der vor-

[2] "Ambitionierte Klimaschutzziele" und "Niedrig-Emissionsszenarien" stehen im Folgenden für Szenarien, in denen die Erhöhung der globalen Durchschnittstemperatur auf 1.5°C bis 2.5°C über dem Niveau vor der Industrialisierung begrenzt ist.

gegebenen Strenge des Klimaziels an. In Niedrig-Emissionsszenarien werden erneuerbare Energien langfristig zur hauptsächlichen Quelle für die Stromproduktion. Modelle mit hohem Anteil an erneuerbaren Energien weisen außerdem besonders hohe Anteile der VRE Wind und Solar auf. Der Vergleich zeigt aber auch deutliche Unterschiede zwischen den in den verschiedenen Modellen berechneten Nutzungsniveaus.

Eine vertiefende Analyse der beiden Solartechnologien Photovoltaik (PV) und solarthermische Kraftwerke (CSP) in REMIND bestätigt die fundamentale Rolle dieser VRE für die Dekarbonisierung des Stromsektors. Aufgrund der in den letzten zehn Jahren erreichten Kostensenkung ist PV mittlerweile in Regionen mit hohem mittäglichem Strombedarf und starker Sonneneinstrahlung konkurrenzfähig zu anderen Kraftwerksneubauten. Die Abbildung der Systemintegrationskosten in REMIND hat einen deutlichen Einfluss auf den Wettbewerb zwischen PV und CSP: CSP mit thermischem Speicher und Wasserstoff-Co-Feuerung kann gesicherte Leistung bereitstellen und hat deshalb niedrigere Integrationskosten als PV, wodurch CSP bei hohen Anteilen an VRE konkurrenzfähig wird.

Eine modellübergreifende Analyse des Verkehrssektors zeigt eine Reihe von unterschiedlichen Emissionsvermeidungsstrategien auf. Unsere Untersuchung bestätigt, dass der Verkehr nur schwach auf CO_2-Preise mittlerer Höhe reagiert: Bis 2050 hinken relative Emissionsreduktionen im Verkehrssektor 10–30 Jahre hinter denen in anderen Sektoren her, und Flüssigtreibstoffe bleiben Hauptenergieträger. Auf längeren Zeitskalen bis 2100 stellt der Verkehrssektor jedoch hinsichtlich ambitionierter Klimaschutzziele kein unüberwindbares Hindernis dar: Bei höheren CO_2-Preisen zeigen die Modelle deutliche Reduktionen der Verkehrsemissionen – falls entweder Wasserstoff-Brennstoffzellen bzw. batteriebetriebene Elektromobile die Nutzung neuer Energieträger mit niedrigen CO_2-Emissionen ermöglichen oder Biotreibstoffe der zweiten Generation (möglicherweise mit CCS) niedrige Emissionen trotz fortgesetzter Nutzung von Flüssigtreibstoffen erlauben.

Die abschließende Studie beschäftigt sich mit dem Zusammenhang zwischen der Strenge eines Klimaschutzziels und den damit verbundenen technischen und ökonomischen Anforderungen und Folgen. Unsere Ergebnisse zeigen, dass die Umgestaltung des globalen Energiesystems, die zur Einhaltung des 2°C-Zieles mit einer Zweidrittel-Wahrscheinlichkeit notwendig ist, zu moderaten ökonomischen Kosten erreichbar ist. Dieses Resultat ist abhängig von der zeitnahen Umsetzung umfassender globaler Emisssionsminderungsmaßnahmen sowie der Verfügbarkeit verschiedener Technologien, die die Marktreife noch nicht gänzlich erreicht haben. Verzögert man die Einführung starker Klimaschutzpolitik, so erhöhen sich die Kosten substantiell, was das Erreichen ambitionierter Klimaschutzziele gefährdet. Wird die heutige schwache und lückenhafte Klimaschutzpolitik beispielsweise bis 2030 fortgeführt, so würden sich die Übergangskosten zur Erreichung des 2°C-Ziels verdreifachen gegenüber einem Szenario, in dem sich die Welt schon 2015 auf ambitionierten Klimaschutz verständigt und somit ab 2020 deutliche CO_2-Reduktionen erreicht. Sollten Schlüsseltechnologien nicht nutzbar sein, so würde sich die Dringlichkeit eines globalen Klimaschutzabkommens noch weiter erhöhen.

In dieser Arbeit wurde eine umfassende Analyse ambitionierter Klimaschutzszenarien und ihrer ökonomischen Anforderungen und Folgen durchgeführt, wobei ein besonderer Fokus auf der Nutzung erneuerbarer Energien einerseits und Emissionsreduktionen im Verkehr andererseits lag. Auf Basis umfangreicher eigener Modellrechnungen und globaler Modellvergleiche liefert die Arbeit entscheidende Erkenntnisse und Strategien für das Erreichen ambitionierter Klimaschutzziele.

Nomenclature

AEII	Autonomous energy intensity improvement
AFR	Sub-saharan Africa
AME	Asian Modeling Exercise
BAU	Business as usual scenario
BECCS	Bioenergy with carbon capture and sequestration
BEV	Battery-electric vehicle
Bio-IGCC	Biomass based internal gasification combined cycle power plants
BRIC	Brazil, Russia, India, China
CBA	Cost-benefit analysis
CCS	Carbon capture and sequestration
CES	Constant elasticity of substitution
CGE	Computable general equilibrium
CHN	China
CSP	Concentrating solar power
DNI	Direct normal irradiation
DSM	Demand side management
EJ	Exajoule
EMF	Energy Modeling Forum
ESM	Energy system model
EU ETS	EU emissions trading system
FCV	Fuel-cell vehicle
FE	Final energy
FLh	Full load hours
GDP	Gross domestic product
GHG	Greenhouse gas
GTI	Global tilt irradiation
GW	Gigawatt
GWP	Gross world product
H_2	Hydrogen
HVDC	High voltage direct current
IAM	Integrated assessment model
IAV	Integrated adaptation and vulnerability
IND	India
IPCC	Intergovernmental Panel on Climate Change
JPN	Japan
LAM	Latin America
LCOE	Levelized costs of electricity generation
LDV	Light-duty vehicle
MAC	Marginal abatement cost
MEA	Middle East and northern Africa
MWh	Megawatt hour
O&M	Operation and maintenance
OAS	Other Asia
PE	Primary energy
POL	Policy scenario
ppm CO_2e	Parts per million CO_2 equivalents
PV	Photovoltaics
RE	Renewable energy
REF	Reference scenario
RES	Renewable energy sources

ROW	Rest of the world
RUS	Russia
SAM	Social accounting matrix
SE	Secondary energy
SM	Solar multiple
SRREN	Special report on renewable energy sources and climate change mitigation
VRE	Variable renewable energy
Wp	Watt-peak

Chapter 1

Introduction

Humanity is interfering with the climate system by emitting greenhouse gases (GHG), thereby threatening its own future welfare. Limiting climate change and stabilizing the temperature requires drastic reductions of GHG emissions to close to zero. As our current system relies on fossil fuels, reducing GHG emissions can only be achieved through a full-scale transformation of the energy system. There are many possible ways how such a decarbonization could be realized, and how the resulting energy-economy system might look like. Different transformation paths require different technologies and changes and will result in different socio-economic and environmental impacts. To make informed decisions about the desired ambition of climate targets and the process of decarbonizing the economy, policymakers need to understand the different requirements and implications of alternative transformation routes.

In this chapter, we first give a brief overview of the current state of knowledge about impacts of climate change (Section 1.1). Section 1.2 is dedicated to basic concepts of the economics of climate change mitigation, including metrics for mitigation costs, different problem framings, as well as a brief review of global model comparison studies that have analyzed economic implications of mitigation. In Section 1.3, we discuss the main tool for studying global economic impacts of climate mitigation, namely integrated assessment models (IAMs). IAMs represent the most relevant dynamics and interactions between the energy system, the economy and the natural sphere in a stylized way. They ensure consistent scenario building and allow scientists to quantitatively estimate key characteristics of transformation pathways, and are therefore crucial for policy assessment. In Section 1.4 we discuss the energy system and present decarbonization patterns of the power sector and the transport sector. Section 1.5 specifies thesis objective and structure, and details how the main research questions are addressed.

The main methodological tool used in this thesis is the IAM REMIND, a hybrid intertemporally optimizing growth model coupled to a detailed energy system model (see Section 1.3.4). This IAM allows the detailed analysis of the structural decarbonization patterns of different parts of the energy system, such as the power sector or the transport sector. Investigating a wide spectrum of options and conditions reveals critical bottlenecks as well as low-hanging fruits for climate change mitigation.

1.1 Climate change

Human economic activity is closely linked to the emission of greenhouse gases. These emissions alter our climate, or, as the summary for policymakers of working group 1 of the 5th assessment report of the Intergovernmental Panel on Climate Change (IPCC) states: "Human influence on the climate system is clear. This is evident from the increasing greenhouse gas concentrations in the atmosphere, positive radiative forcing, observed warming, and understanding of the climate system". Moreover, the IPCC claims that "It is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century" (IPCC, 2013). Among scientific publications, there is an overwhelming consensus that climate change is strongly driven by anthropogenic influence – a recent study found that out of the ∼4000 papers published between 1991 and 2011 that express a position on anthropogenic global warming, 97% endorse the position that humans cause global warming (Cook et al., 2013).

Unmitigated climate change will likely lead to a further mean global sea level rise by 52–98 cm until 2100, further loss of global glacier volumes by 35–85%, and an increase of intensity and duration of droughts (IPCC, 2013). It is very likely that frequency and duration of heat waves increase over most land areas, and that frequency and intensity of extreme precipitation events increases over most of the mid-latitude land masses and over wet tropical regions.

All of these climatic changes will have major effects on human societies that have evolved and adapted their infrastructure in response to a certain climatic situation. For example, many of the major metropolitan areas are situated close to the sea or in river estuaries. Hence, a sea level rise can impact these centers of economic activities, possibly leading to disruptive secondary effects. Loss of glacier volumes will in the long term endanger the drinking and irrigation water supply for the people living in their watersheds, which make up about 1/6th of the global population (IPCC, 2007). The increase in frequency and intensity of droughts and extreme precipitation events will harm the agricultural sector and possibly lead to regional famines.

The existence of "tipping elements" makes it advisable to follow a precautionary principle approach to climate change mitigation. Tipping elements can be described as qualitative changes to large components of the climate/ecosphere once global warming reaches a certain threshold temperature. These changes strongly increase either climate change itself or its effects (Lenton et al., 2008). Examples include the thawing of permafrost soil releasing methane, the melting of the Greenland ice sheet leading to substantial sea level rise, or the collapse of the Amazonian rain forest influencing regional ecosystems and precipitation patterns.

In a recent World Bank study called "Turn down the heat: why a 4°C warmer world must be avoided", the authors discuss a number of risks that unmitigated climate change poses to ecosystems and human societies (World Bank, 2012). While acknowledging that uncertainties are still large, they come to strong conclusions: "[...] a 4°C world is so different from the current one that it comes with high uncertainty and new risks that threaten our ability to anticipate and plan for future adaptation needs. The lack of action on climate change not only risks putting prosperity out of reach of millions of people in the developing world, it threatens to roll back decades of sustainable development."

1.2 Economics of climate change mitigation

From the above it seems clear that letting the world continue on a path towards unmitigated climate change is not an option. Article 2 of the United Nations Framework Convention on Climate Change accordingly defines its objective "to achieve [...] stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system" (UNFCCC Secretariat, 1992). The conference of the parties specified the ambition of "reducing human-generated greenhouse gas emissions over time to keep the global average temperature rise below two degrees" (UNFCCC Secretariat, 2011). Stabilizing the global temperature increase at a certain level implies a corresponding cap on cumulative GHG emissions (Matthews and Caldeira, 2008; Matthews et al., 2009; Meinshausen et al., 2009), which can only be achieved by decarbonizing the energy system.

Deciding on a level of ambition for the climate target opens up new questions. For any given climate target, there are a multitude of possible transformation pathways with different requirements and (economic) implications. These pathways to decarbonization span a large solution space: they result in different costs for different nations and populations, rely on different technologies, require different transformations of the economy, imply different risks, and are more or less flexible towards policy revisions.

At the same time, a number of different objectives compete with each other, including lowest total cost, distributional impact, other sustainability challenges, reduction of risk of failure. Weighting these different objectives is beyond the reach of science, and needs to emerge from an informed process of public debate and policy choice. What science can contribute, however, is the exploration of the various implications, including economic ones, of different paths in the solution space of mitigating climate change. Such an exploration can provide a sound scientific basis pointing out the most relevant trade-offs, which enables policymakers to weigh the various benefits and costs of differing mitigation targets and decarbonization pathways, and to decide which route to follow.

To provide this scientific basis and identify and assess the most relevant economic trade-offs of climate change mitigation, IAMs have turned out to be a useful tool, which we will discuss in detail in Section 1.3 (Nakicenovic et al., 2000; Hourcade and Shukla, 2001; Fisher et al., 2007; Barker et al., 2007; Weyant, 2009). IAMs are computer models that represent the energy system, the economic sphere, and a simplified link to or representation of the climate system, with optional further links to other relevant spheres such as the land-water nexus, air pollution or ecosystem services. They are used to develop self-consistent scenarios of how the world might develop under different mitigation policies and socio-economic assumptions (Morita and Robinson, 2001; Fisher et al., 2007). Comparing these scenarios allows analyzing the changes to the energy and economic system that are required to achieve an aspired mitigation target, and to deduce the techno-economic impacts and requirements of different mitigation targets.

1.2.1 Metrics for economic implications and costs

Comparing scenarios with different levels of climate policy allows quantifying the economic costs incurred by reducing emissions. As the decarbonization of the economy will

have impacts across a variety of sectors and market actors, a number of different metrics for **mitigation costs** at different aggregation levels are commonly used (Hourcade et al., 1996b; Markandya and Halsnaes, 2001; Edenhofer et al., 2006).

Most detailed are **direct engineering costs**, which represent the explicit costs of a technical measure that is implemented to reduce emissions. In contrast, **sector-specific costs** look at a larger number of mitigation measures and substitutions within one sector, thus taking a partial equilibrium view. If one also includes general equilibrium effects, i.e. economic feedbacks between sectors, one arrives at macro-economic mitigation costs. The most commonly used metric for such costs are **consumption losses**: the difference between the cumulated discounted total consumption in the climate policy and in a reference scenario, usually stated relative to cumulated discounted gross domestic product (GDP) or consumption to allow a more intuitive understanding. **Welfare costs** go one step further: they include the basic welfare-economic notion that marginal utility of consumption decreases as consumption increases, and therefore consumption losses over(under)estimate the actual welfare effects at high (low) per capita consumption levels (Edenhofer et al., 2006). Besides changing total GDP or consumption of a country, mitigation efforts will also directly influence **energy prices**. Energy prices are a tangible metric, as they are directly borne by the population. Thus they can serve as a relevant metric to gauge public reaction to climate policies. Furthermore, energy expenditures are regressive, such that mitigation-induced energy price changes capture some of the distributional effects of climate change mitigation.

1.2.2 Cost-benefit vs. cost-effectiveness analysis

From an economic point of view, an action can be evaluated by looking at all its current and future costs, and weighing them off against all the current and future benefits it brings. This is the principle embodied in **cost-benefit analysis (CBA)**, a tool that is often employed to evaluate whether or not public projects should be pursued (Layard and Glaister, 1994; Arrow et al., 1996b; Mishan and Quah, 2007). In the realm of climate change, CBA might theoretically be used to derive a climate mitigation target according to the following logic: the optimal amount of mitigation is reached when the marginal cost of mitigating an additional ton of CO_2 is equivalent to the marginal damage this ton of CO_2 would cause in climate damages – at least in theory, if all direct and indirect damages and costs were known with full certainty and could be aggregated in a consistent way (Munasinghe et al., 1996).

While CBA is widely used for the appraisal of public projects, e.g., infrastructure investments, it is of limited use for climate change mitigation. Some IAMs were used to perform CBA of climate change mitigation (Nordhaus, 1993; Peck and Teisberg, 1995; Manne et al., 1995; Nordhaus and Boyer, 2000), but this approach has been criticized for a number of reasons (Munasinghe et al., 1996; van den Bergh, 2004; Ackerman et al., 2009). As CBA remains a focus point for policymakers and the discussion about its use for climate change mitigation resurfaces from time to time, we list some of the most critical issues in the following.

First of all, the exact nature and incidence of climate damages is fraught with uncertainty, and the way this uncertainty is dealt with can substantially influence the results (Ackerman

and Munitz, 2012). The monetization of climate damages strongly depends on the choice of method and requires a multitude of controversial ethical assumptions, such as whether or not the value of lost life years scales with income (Pearce et al., 1996).

Aggregating costs and damages for a CBA requires some assumption about how future costs and benefits are discounted, which is a very controversial issue (Rabl, 1996; Arrow et al., 1996a; Markandya and Halsnaes, 2001; Halsnaes et al., 2007; Brekke and Johansson-Stenman, 2008; Dasgupta, 2008; Ackerman et al., 2009; Roemer, 2011). Climate change impacts are most severe in the far future, while mitigation costs would apply immediately. Therefore, the higher the chosen discount rate, the less important climate damages appear compared to mitigation costs. While some argue that discount rates should be derived from observed interest rates in markets, which leads to comparatively high discount rates (Nordhaus, 2007), others argue that observed market behavior is unsuited for the evaluation of long-term societal decisions, and that based on philosophical arguments much lower discount rates should be used (Stern, 2007).

Also, from the exponential form of discounting in combination with the uncertainty about the real discount rate it can be derived that for long-term analyses, a declining discount rate should be used (Arrow et al., 2013) – which is in contrast to current IAM conventions.

According to Weitzman's Dismal Theorem, fat-tailed distributions of climate change parameters together with nonlinear climate damages can dominate the discounting procedure and lead to substantially higher expected climate damages than one would calculate using only the average values (Weitzman, 2009). This poses an issue to IAMs, which mostly use average values instead of the full probability distribution functions due to numerical complexity, and thus underestimate climate damages. This issue can be compounded by the mathematical specification of the welfare function in some cost-benefit IAMs, namely the link between risk aversion and preference towards intergenerational transfers (Kaufman, 2012).

Aggregating costs and benefits across space also poses substantial challenges for both modelers and policymakers, as it raises fundamental questions about equity (Banuri et al., 1996; Banuri and Weyant, 2001; Toth and Mwandosya, 2001; Halsnaes et al., 2007; Gupta et al., 2007). Most optimizing IAMs that model more than one region utilize the "Negishi Weight" mechanism (Negishi, 1972; Manne and Rutherford, 1994). This process ensures that the optimized model result equals the market equilibrium, but it can also be described as attaching greater weight to the welfare of richer regions to prevent capital transfers from rich to poor regions (Stanton et al., 2009; Stanton, 2011).

Although the mostly techno-economic nature of mitigation reduces many of the monetization issues of climate damages, IAMs might overestimate the difficulties of reducing CO_2 emissions as they are usually calibrated on trends and technologies based on observations in a past where there were no incentives for emission reductions, thus they did not matter. Many IAMs do not represent the changing nature of socio-economic systems, which will adapt to new incentives through several mechanisms such as endogenous technological change or the effect of expectations on investment (Ackerman et al., 2009; Jaeger et al., 2011).

Some IAMs have begun to endogenize technological change for specific sectors and technologies (Weyant and Olavson, 1999; Grubb et al., 2002; Edenhofer et al., 2006; Gilling-

ham et al., 2008), but a full integration of endogenous growth and socio-economic evolution in IAMs is still missing.

By instead performing **cost-effectiveness studies**, which analyze the economic costs of achieving a given climate or emission target, some of these issues can be circumvented (Munasinghe et al., 1996; Hourcade et al., 1996a; Toth and Mwandosya, 2001; Ackerman et al., 2009). In such scenarios, the difficulty of monetizing climate damages is avoided and the impact of the discount rate is reduced (Munasinghe et al., 1996; Ackerman et al., 2009; Luderer et al., 2013b). In the last decade, the cost-effectiveness approach has become the norm for IAMs: most model comparison projects (including all studies in this thesis) assume a certain climate policy as given, and calculate cost-effective paths to achieve this policy.

1.2.3 Economic implications of climate change mitigation – results from recent model comparison projects

Model comparison projects employing a number of IAMs are a crucial instrument for assessing mitigation policies and their economic implications. In these model comparison projects, international research groups define a number of scenarios with different boundary conditions, such as climate target stringency, technology availability, or international cooperation. These scenarios are then run by all participating IAMs to see if robust findings emerge, or if differences can be traced back to different model assumptions. Here we briefly list the results from some of the most important comparison projects finished in the last years, namely **ADAM** (Edenhofer et al., 2010b), **EMF22** (Clarke and Weyant, 2009), **RECIPE** (Edenhofer et al., 2012), **AME** (Calvin et al., 2012a), and **EMF27** (Kriegler et al., 2014).

The **ADAM** project focused on the cost and achievability of stringent climate targets based on availability of aggregated technology classes (Edenhofer et al., 2010a; Knopf et al., 2010). All analyzed models showed technical and economic feasibility of stringent climate targets, with aggregated mitigation costs of below 2.5% of GDP for scenarios limiting GHG concentrations to 400 parts per million CO_2 equivalents (ppm CO_2e). Excluding renewables from the technology portfolio was found to have the highest impact on mitigation costs, followed by the exlcusion of carbon capture and sequestration (CCS).

The **Energy Modeling Forum study EMF22** analyzed the effect that delayed participation by certain global regions has on climate mitigation scenarios (Clarke and Weyant, 2009). The analyzed scenarios entailed UNFCCC Annex I countries mitigating emissions immediately, the BRIC states (Brazil, Russia, India, China) implementing mitigation policies after 2030, and the rest of the world joining in 2050. Such a substantial delay strongly increased mitigation costs for weak climate policy targets and made achieving a climate target with 450 ppm CO_2e concentration in 2100 impossible for all but two out of the total of fourteen models.

RECIPE turns the focus on a number of second-best complications that exist in the real world but were only insufficiently represented in early IAMs, such as inertia, path-dependencies of infrastructure investments, or myopic behavior (Edenhofer et al., 2012). For aggregated mitigation costs, the results confirm earlier findings: as long as the international community takes immediate action to mitigate climate change, the total mit-

igation costs of intermediate climate stabilization targets are below 2% of global GDP. Delaying global climate policy until 2030 would push the 450 ppm CO_2 target out of reach, and renewables and CCS are found to be the most important technologies for mitigation (Luderer et al., 2011). When a strongly myopic behavior is assumed, very high initial carbon prices are required to initiate the trend-break necessary for low climate stabilization (Waisman et al., 2012). Also long-term costs can be substantial due to difficult decarbonization of the transport sector (Luderer et al., 2011), but additional infrastructure policies can induce shifts to public transport modes and thereby reduce mitigation costs substantially (Waisman et al., 2012).

The **Asian Modeling Exercise (AME)**, which Chapter 2 of this thesis is part of, focused on the role of Asia for global climate change mitigation, with specific diagnostic attention to the impact of regional socio-economic characteristics (Calvin et al., 2012a). While differences between regions influence the results in all models, it was also observed that differences between models can be larger than differences between regions (Clarke et al., 2012), with some models exhibiting dominant technologies and strong regional convergence that might be seen as "model fingerprints". Also, reasons for differing base year assumptions were identified (Chaturvedi et al., 2012), and the range of different model baseline scenarios was analyzed and compared to historical values (Blanford et al., 2012). A comparison of nationally set targets (the Copenhagen pledges) to the modeling results for different global climate targets found that some of the national targets seem to have low ambitions, as they are reached even in the baseline scenarios of several models (Calvin et al., 2012b).

The **Energy Modeling Forum study EMF27**, which Chapter 3 of this thesis is part of, analyzed the role of individual technology groups for the achievability and cost of different mitigation targets (Kriegler et al., 2014). A large number of models ran a matrix of scenarios that differed in their assumptions about the availability and cost of major technology groups such as nuclear, CCS, variable renewables, and biomass, as well as about additional energy efficiency improvements. Given full technology availability, all models but one were able to achieve a stringent 450 ppm CO_2e target (consistent with the 2°C target) at aggregated discounted mitigation costs below 3.5% of baseline GDP. Limiting technology availability had a marked impact on target achievability and cost, with highest cost increases resulting from the exclusion of CCS, followed by the scenarios with limitations on biomass use (Krey et al., 2014).

1.3 Integrated Assessment Models

IAMs[1] combine the socio-economic sphere with natural sciences to analyze long-term interdisciplinary questions such as assessing policies to mitigate climate change (Van Vuuren et al., 2011a). They are the workhorse of quantitative research about the economics of global mitigation. IAMs can be very different in size and scope, ranging from ex-

[1] In this thesis, we mostly use the term "IAM", but the terms "Energy-Economy-(Environment/ Emissions/ Climate) Model" or "E3 Model" are also frequently used in the research community. Although much wider classes of IAMs exist, in the context of climate change they usually consist of an energy-economy model that at least tracks emissions, but often also is coupled to a reduced-form climate module plus possibly other modules for land use, material flows, etc.

tremely aggregated and thus mathematically simple models like DICE (Nordhaus and Boyer, 2000) to extremely detailed models like IMAGE (Bouwman et al., 2006; van Vuuren et al., 2010), GCAM (Calvin et al., 2011; Edmonds et al., 2013), MESSAGE (Messner and Schrattenholzer, 2000; Krey and Riahi, 2009), AIM (Kainuma et al., 2003), or REMIND-MAgPIE (Popp et al., 2010; Luderer et al., 2013a,b). DICE can be used to quickly explore a large parameter space and helps to understand basic dynamics and interactions between climate policy and the economy, but the exact results can be dominated by the simplifying assumptions and thus should not be taken at face value. The large-scale models manage to create a much more detailed representation of the relevant interactions in the different subsystems, but due to their complexity are much more challenging to use, modify, and understand (Craig et al., 2002; DeCarolis et al., 2012).

1.3.1 Purpose of IAMs

The main objective of IAMs in the context of climate change is to produce self-consistent scenarios of how the future might unfold in several key spheres, namely the energy system, the economy, GHG emissions and the climate system. These scenarios are useful to assess mitigation targets, the possible strategies to achieve them and the economic costs they entail (Hourcade et al., 1996a; Nakicenovic et al., 2000; Morita and Robinson, 2001; Sims et al., 2007; Barker et al., 2007; Moss et al., 2010; Van Vuuren et al., 2011b). They can be seen as focus points that allow identification, discussion and analysis of economically relevant decisions, they point out bottlenecks where envisioned transformations might fail, and they help to prioritize the most pressing questions for further research (Abaza and Baranzini, 2002; Weyant, 2009; Moss et al., 2010; Edenhofer et al., 2012). IAMs should not be mistaken for crystal balls that try to foretell the future (Smil, 2000b; Craig et al., 2002). Rather, they help to construct plausible scenarios that are internally consistent, meaning that they respect the many interactions perceived by the modeler to be crucial, and monitor stocks and flows of both physical and economic quantities (Nakata, 2004). IAMs are therefore useful tools for policy advice and assessment. They can assist by scanning the full spectrum of options and determining the crucial technological, economic and political factors that influence the achievability of climate targets (Craig et al., 2002; Edenhofer et al., 2010a; DeCarolis, 2011). IAMs can point out important trade-offs and necessary decisions between different objectives, such as total cost, distributional effects, or other sustainability indicators.

Within the approaches used to study the economic implications of emission reductions, IAMs have important advantages over other methods such as sector-specific studies or marginal abatement cost (MAC) curves: IAMs can incorporate both the sectorial interactions, the regional interactions, as well as the path-dependencies and inertias seen in the real world (Kesicki and Strachan, 2011; Morris et al., 2012). Sector-specific studies can analyze decarbonization options within one sector in high detail, but they omit the feedbacks that a change within one sector can have on prices, as well as the interactions between decarbonization options in different sectors (Kim et al., 2006). MAC curves represent a single point in time; they try to estimate what a certain emission reduction that is achievable through a certain technology deployment or other measure would cost. However, these costs, as well as the size of possible emission reductions, fundamentally depend on what happened in the past. Most energy technologies are long-lived,

and replacing them outside their normal depreciation schemes comes with substantial cost increases. Developing and upscaling new low-carbon technologies requires decades – the emission reductions achievable in a certain year thus depend on whether the technology deployment process was started five or twenty years earlier.

IAMs are neither prescriptive nor comprehensive – their results should be evaluated in conjunction with other non-modeled factors influencing policy decisions, such as ethical premises, social preferences, as well as institutional capacities and limitations.

IAM scenarios also serve as vital input for the research performed by the climate and integrated adaptation and vulnerability (IAV) modeling communities (Van Vuuren et al., 2011a): "In turn, IAMs provide to the climate modeling community emissions scenarios of greenhouse gases (GHGs) and short-lived species (SLS) and land-use projections. IAMs provide to the IAV modeling community projections of socioeconomic states, general development pathways, and the multiple stressors of climate change" (Janetos, 2009).

1.3.2 Right or Wrong – the art and science of IA modeling

A more detailed model is not necessarily a better model (Craig et al., 2002). The art and science of IA modeling consists of determining and modeling the interactions and dynamics most relevant for a specific problem or research question, and omitting the details that are not relevant (Epstein, 2008). It is not only technically impossible to include all details about a certain sector or technology, it can actually reduce usability of the model, as too much detail potentially swamps the relevant results. The aim of IA modeling is to reproduce the characteristic patterns of sectorial decarbonization, not to include as many subcategories of technologies as possible. Another danger of trying to include all subsector details is that it can create a misleading sense of certainty (Morgan and Keith, 2008).

This does not mean that IAMs are created in a void – their aggregated representations of interactions and dynamics rely on the existence of more detailed disciplinary and sectorial knowledge from which stylized facts can be extracted (Abaza and Baranzini, 2002; Derr and Patrick, 2009; Bhattacharyya and Timilsina, 2010). An illustrative example: Changing the energy system will likely require new investments into energy infrastructure, such as grids or pipelines. An IAM cannot calculate these costs directly, as it does not have a sufficient spatial detail: a model representing the EU as a copper plate cannot endogenously determine the additional EU-internal grid investments arising from large-scale renewable deployment. To do this, bottom-up models with higher spatial detail are required (Weigt et al., 2010; Leuthold et al., 2012; Schaber et al., 2012; Becker et al., 2013). From a large number of detailed calculations, it should then be possible to extract generalized scaling rules that can be implemented in the IAM to roughly represent the detailed costs. Accordingly, there needs to be a constant two-way dialogue between IAMs and more bottom-up research. Better understanding of the detailed dynamics inside a sector or subsystem informs the aggregated representation in IAMs, while IAMs provide the relevant system states (surrounding conditions and interactions, including future demands and scarcities or expected prices) that might become relevant in the future and therefore should be investigated in more detail (Schneider, 1997).

On a fundamental level, IAMs are formed by their modelers – explicitly or implicitly, the modeler's perception of the world shapes how the IAM is formulated, which interactions and dynamics are deemed relevant and therefore programmed into the code, and which are seen as less relevant and therefore omitted to reduce numerical complexity (Keepin and Wynne, 1984; Craig et al., 2002; van der Sluijs, 2002). Their nature as scenario-producing tools makes it difficult to test IAMs against the future development of the world and find "the right one" – no one can foresee how adaptive economies are, which technology will evolve how, which policies will be implemented when (Craig et al., 2002; Weyant, 2009; Scher and Koomey, 2011; DeCarolis et al., 2012). Hence, there exists a certain space for "a modeler's choice". The analysis of decisions about climate change mitigation requires value judgments about inter- and intra-generational equity that cannot be determined scientifically, such as appropriate discount factors, equity weights, or technology risks (Schneider, 1997; Craig et al., 2002; van der Sluijs, 2002; Risbey et al., 2005; Edenhofer et al., 2012).

If an IAM is only calibrated to past and current micro-states of the different energy and economic subsystems, it is of little use for analyzing climate mitigation scenarios, as in these scenarios a hitherto unknown driver changes the world from the state we currently know: the (priced) scarcity of carbon dioxide emissions (Craig et al., 2002; Nakata, 2004). On the other hand, if an IAM produces scenarios that in the short to medium term do not respect currently known technical and economic restrictions and are therefore implausible, it has little value for either science or policy advice.

It is therefore important to continuously analyze IAMs and their results and ask "is this a bug or a feature? Are certain results an interesting and relevant outcome of the modeled interactions, or are they an unwanted by-product of simplifications that should be changed to increase plausibility?" (Derr and Patrick, 2009; Bhattacharyya and Timilsina, 2010; DeCarolis et al., 2012) A valuable tool both for testing and improving IAMs and for making them more useful for policy advice are model comparison exercises, two of which can be found in Chapters 3 and 5. For one thing, they force modelers to critically assess and explain the results of their models and to determine the reasons for diverging results. Additionally, they capture some of the real-world uncertainty that often cannot be included in one model, and thus prevent the fallacy of accepting a model's results as a true projection of the future (Craig et al., 2002).

1.3.3 IAM typology

Energy-economy-emission-models used for analyzing long-term climate policies can be classified according to different schemes (Kydes et al., 1995; Sanstad and Greening, 1998; Hourcade and Shukla, 2001; Barker and Srivastava, 2001; Nakata, 2004; Hourcade et al., 2006; Edenhofer et al., 2006; Stanton et al., 2009). One insightful way of categorizing them is to trace them back to four fundamental model types (Edenhofer et al., 2006): i) **computable general equilibrium models**, which focus on a detailed representation of the individual sectors of an economy, ii) **optimal growth models**, which focus on the optimal long-term evolution of macro-economic variables, iii) **energy system models**, which try to represent the energy system at a high level of detail and disaggregation, and iv) **econometric/simulation models**, which deterministically project aggregated state variables based on time series from the past or differential equations. Furthermore, the

attributes "**top-down**" and "**bottom-up**" are sometimes used to additionally classify models, with top-down models focusing more on economic effects and – due to their aggregated nature – relying strongly on parameterization, while bottom-up models use a more detailed, technology-level description that is based on engineering data (Hourcade and Shukla, 2001; Barker and Srivastava, 2001; Nakata, 2004; Hourcade et al., 2006). The model type can have a large influence even on the aggregated results: "Still, one relatively robust feature with the models included in the study is that the technology rich models (in this case the bottom-up models ETSAP-TIAM, IMAGE, MESSAGE, MiniCAM) show a lower cost of meeting a 550 ppm CO_2e target without overshoot as compared to models with less technological details" (Hedenus et al., 2013). In the following, we will outline some basic characteristics of the four model types:

Computable general equilibrium (CGE) models like EPPA (Paltsev et al., 2005), the GTAP model (Hertel, 1999), SGM/Phoenix (Brenkert et al., 2004; Fisher-Vanden et al., 2012), GEM-E3 (Capros et al., 2013) or WorldScan (Lejour et al., 2006), follow the circular flow of the economy and can be traced back to the input-output models developed by Leontief (Dixon and Jorgenson, 2012). In the late 1950s, Leif Johanson extended this approach by adding functional forms for the substitution between input factors, adding demand/production functions for households and firms and endogenizing prices (Dixon and Jorgenson, 2012). The basis of a CGE are the social accounting matrix (SAM) mapping all the monetary flows of the economy, as well as the market clearing condition for production factors and commodities, the zero-profit condition for firms and the budget constraint for households (Mathiesen, 1985; Sue Wing, 2004, 2009). CGEs are calibrated to the SAM representation of the base year and can be used to analyze statically how an external shock to one variable affects all other variables in the model. To produce a scenario that spans more than one point in time, they are solved repeatedly, and the outputs of the static solution of one time step plus some externally prescribed time-evolution of GDP and technology parameters are taken as input for the next solution. This process is termed "recursive-dynamic".

As CGEs usually model a large number of economic subsectors and the commodity flows between them, they are useful for an analysis of the differentiated impacts that policies (such as a trade tariffs, or a carbon tax) would have on different economic subsectors. However, the initial benchmarking to the base-year SAM and their reliance on constant elasticity of substitution (CES) functions imply that the initially observed flows can have a determining impact on the future evolution of the system (Clarke et al., 2012). This raises questions about their suitability for the development and analysis of long-term scenarios that try to project trend breaks and paradigm shifts, such as would occur in a world trying to achieve climate stabilization.

Optimal growth models like DICE or MIND (Edenhofer et al., 2005) follow a different approach. They are based on neoclassical growth theory and apply the Ramsey-Cass-Koopmans framework (Ramsey, 1928; Koopmans, 1963; Cass, 1965; Maussner and Klump, 1996). These models endogenize savings and consumption in order to maximize intertemporal welfare, which for mathematical reasons is usually taken to be the logarithm of consumption. Growth models are used to develop intertemporally optimal long-term scenarios that might be seen as benchmarks of what unlimited foresight and optimal policy instruments might achieve. They can therefore be useful for climate policy advice and assessment: they highlight the importance of long-term goals for short-term actions and

set an aspirational goal. On the other hand, pure optimal growth models usually take an aggregated view of the economy and the energy system, and are thus less suited for a detailed sectoral analysis of the requirements and implications of climate change mitigation.

Energy system models (ESM), including the MARKAL/TIMES model family (Loulou et al., 2004; Loulou and Labriet, 2008), MESSAGE, GCAM, POLES (Criqui et al., 1999; Kitous et al., 2010), PRIMES (Capros, 2004; Capros et al., 2014), LEAP (Heaps, 2008), OSEMOSYS (Howells et al., 2011), GET (Azar et al., 2003, 2006), REEDS (Short et al., 2009), LIMES (Haller et al., 2012) and many others, focus on a detailed partial-equilibrium representation of the energy sector. While some ESMs are simulation models, most employ an optimization framework and are used to design a cost-minimizing energy system. They depict the stocks and flows between final energy (or even energy service) demands and primary energy inputs by modeling numerous energy conversion technologies that link the different energy types. ESMs are based on engineering input data for costs and efficiencies of conversion technologies, and usually assume exogenously fixed final energy demands, although some ESMs include price responses to achieve a more realistic model behavior. When focusing on the electricity sector, ESMs usually implement more temporal detail than the other IAM model types, which model time steps of 1–10 years. The reason for this is that electricity is difficult to store and thus not a homogeneous good in time: It is not only the total amount of electricity produced over a year that is relevant, but also when it is produced[2] (Steiner, 1957). Therefore, many ESMs implement two to thirty so-called "time slices" representing characteristic times of a year with different load values and renewable production, or even represent each hour of the year. ESMs are well suited for developing a detailed understanding how energy systems react to policies such as a carbon price. However, their use becomes limited when analyzing stringent long-term mitigation paths or other trend-breaking scenarios. They do not include the feedback of high energy prices on economic growth, and often do not include price-responsive energy demands. Also, deep emission reductions will likely lead to a changing relevance of different economic sectors, resulting in changing demands for energy services.

Simulation/econometric models include a wide range of different model types, which all repeatedly use differential equations to calculate the state variables for the next time step from the state variables of the current state of the world. These equations can either be developed from first principles or be based on econometric time series. In contrast to CGE models, they do not necessarily assume general equilibrium; in contrast to growth models, they have no long-term foresight and intertemporal optimization. The differentiation to energy system models is more a question of focus (whole economy vs. energy system) than of methodology, as many ESMs also use econometrically derived functions to project future energy demands. Examples of this model type include World3 (Meadows et al., 1972), IMAGE or E3MG (Kohler et al., 2006; Barker and Serban Scrieciu, 2010).

Hybrid models have started to blur this separation of model types, which was never very strict to start with. Over time, more and more groups have combined aspects from different modeling approaches or coupled different models to each other (McFarland et al., 2004; Horne et al., 2005; Bataille et al., 2006; Ghersi and Hourcade, 2006; Hourcade et al.,

[2]Electricity is also not homogeneous in space, thus the where of production and demand is also relevant, but only very few of the IAM models focus on this aspect. It will be further discussed below in Section 1.4.1.

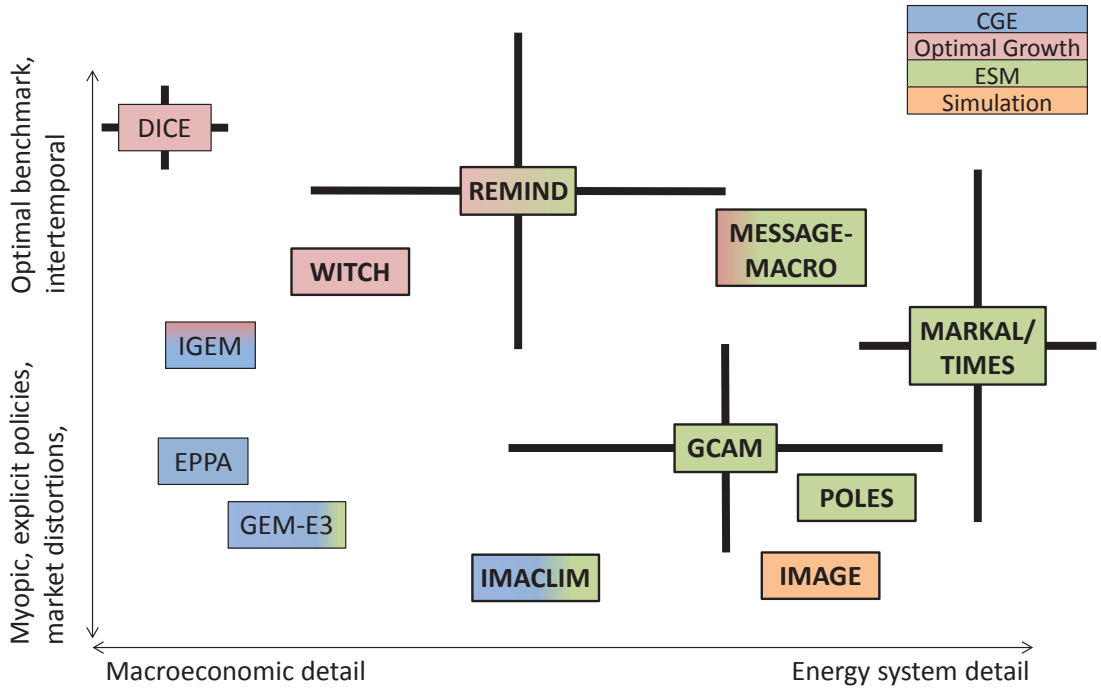


Figure 1: Own estimation of how various IAMs rank along two aggregated axes, namely energy system focus vs. economic focus, and focus on short-sightedness and market distortions vs. focus on intertemporally optimal first-best solution. Color-coding denotes the main model types, and shows some clustering of the models according to their types. Models written in bold are included in the studies presented in Chapters 3 and 5. Models don't have an exact position but can show some flexibility through addition or exchange of sub-modules, which is exemplified with range bars for a few select models.

2006; Böhringer and Rutherford, 2008). Some optimal growth models have added quite detailed energy systems, e.g., REMIND, MERGE (Manne and Richels, 2005), WITCH (Bosetti et al., 2006); some CGE models were augmented with ideas from optimal growth models (IGEM (Goettle et al., 2007), G-cubed (McKibbin and Wilcoxen, 1999)), or from energy system models (IMACLIM (Waisman et al., 2012), AIM/CGE & AIM/Enduse (Kainuma et al., 2003)); some energy system models were enhanced by macro-economic feedbacks (MESSAGE-MACRO (Messner and Schrattenholzer, 2000), PRIMES), simulation models used detailed energy systems modules (IMAGE-TIMER) or introduced limited optimization frameworks (E3MG).

In addition to these four model types, a number of further categorizations can help to differentiate the models and understand better which models are suited for which research questions. As just one example, we show in Figure 1 how some of the models named above might be ranked in a two-dimensional matrix. As y-axis we use the "model world view" – does a model focus on myopic behavior and market failures, or is it used to find the intertemporally optimal first-best solution as a benchmark, and thus takes a more normative approach? The other dimension sorts the models according to their focus on economic detail in contrast to energy system detail. While three of the main model types tend to cluster in certain areas of the diagram, it should be emphasized that the models' behavior can be more flexible: many modeling groups can add or change individual submodules of an IAM und thereby tune the IAM for specific problems and research ques-

tions, for example including the effect of market failures in an optimal growth model. This is shown for a few exemplary models with range bars.

1.3.4 The REMIND model

To address the research questions of this thesis, we employ mainly the REMIND model developed at the Potsdam Institute for Climate Impact Research (Leimbach et al., 2010). It is a hybrid model that combines an intertemporal growth model with a detailed energy system model and a simplified representation of the climate system. It can also be soft-coupled to the agriculture/land-use model MAgPIE (Klein et al., 2014). A detailed description of REMIND can be found in the model documentation (Luderer et al., 2013a). REMIND represents the world in 11 regions and runs until 2100. This long time horizon is necessary for the analysis of climate change mitigation: Given the substantial GHG emission growth over the last decade and assuming realistic rates of change for energy-economic systems, reduction of emission to close to zero will not happen before the second half of the century (Rogelj et al., 2011; Matthews and Solomon, 2013).

The economy is represented by a nested CES production function (see Figure 2). The energy system module represents capacity stocks of more than 50 conventional and low-carbon energy conversion technologies, including technologies for generating negative emissions by combining bioenergy with carbon capture and sequestration (BECCS). REMIND accounts for relevant path-dependencies, such as the build-up of long-lived capital stocks allowing the analysis of embedded emissions and stranded investments (Bertram et al., 2014), as well as learning-by-doing effects and inertias in the up-scaling in innovative technologies. By explicitly representing the scarcity of energy resources (fossil, nuclear, biomass and available land for solar and wind) and international trade, it endogenously calculates the reaction of resource prices to climate policies and other scenario assumptions.

1.4 Decarbonizing the energy system

Substantially reducing GHG emissions necessarily implies decarbonizing the energy system, as energy system emissions account for about 66% of all anthropogenic GHG emissions in 2004 (IPCC, 2007). Figure 3 shows a sketch of the US energy system to exemplify the energy flows and transformations from primary energies on the left to energy services on the right. Common to most energy systems in developed and emerging economies is the important role of electricity generation, the use of solid, liquid and gaseous fuels to provide heat for the stationary sector (combining residential, commercial and industrial), and the reliance of the transport sector on liquid fuels to provide mobility.

1.4.1 Power sector

When analyzing the decarbonization of the energy system, the electric power sector has a pronounced position: It accounted for 41% of all energy-related CO_2 emissions in 2010

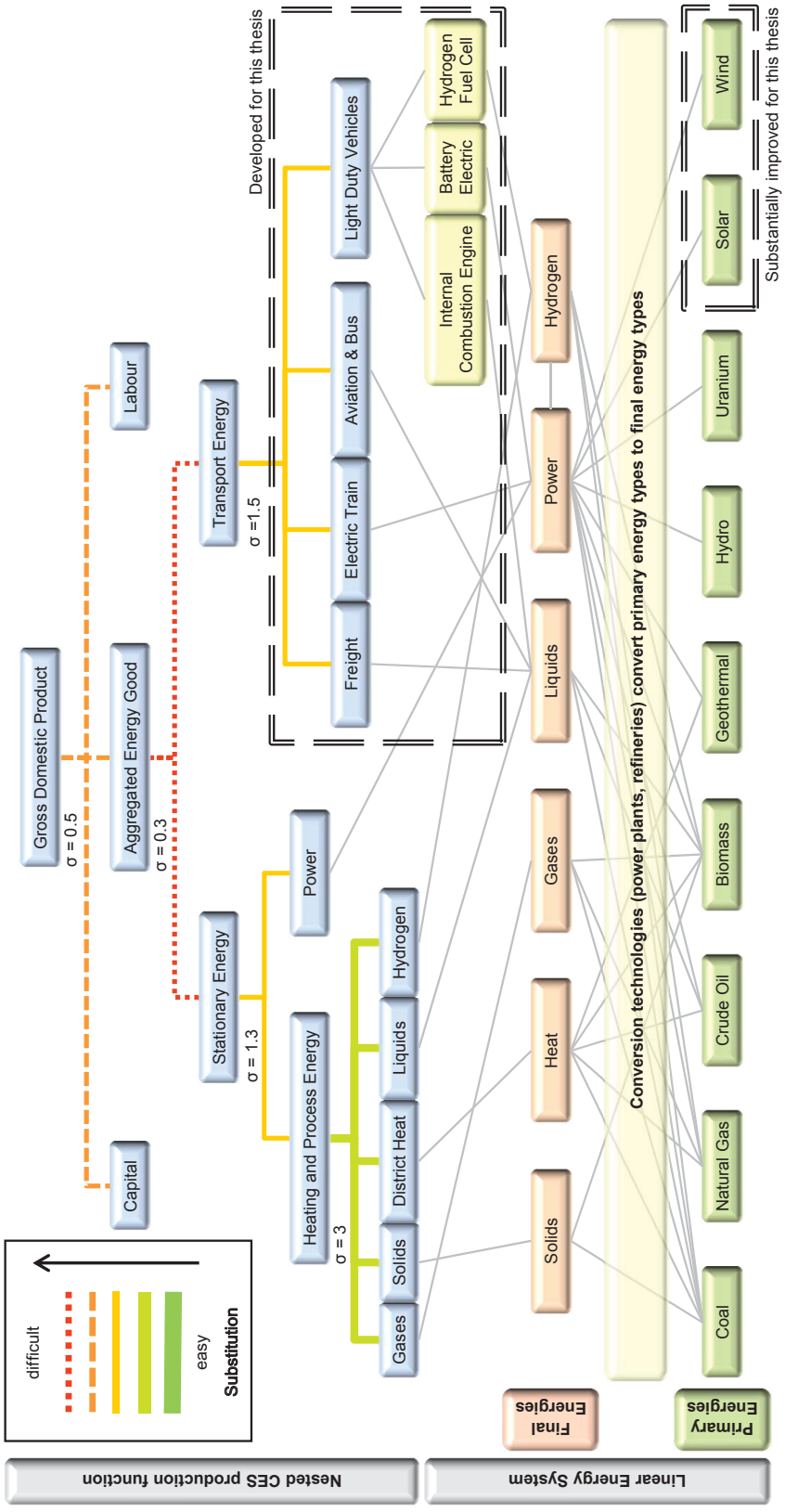


Figure 2: Schematic of the energy and economy modules of REMIND. The lower part shows the linear energy system with a large number of conversion technologies. Substitution between different technologies is linear, and capital stocks of conversion technologies are tracked, thus creating path dependencies. The upper part shows the economy in form of a nested CES production function with limited substitutability and no path dependency. The substitution elasticity σ determines how easy it is to substitute to input factors for each other, with σ=0 meaning no substitution possible (Leontief production function), σ=1 meaning that input factor can asymptotically substitute for each other (Cobb-Douglass production function), and σ=infinity meaning full substitution between input factors (linear production function).

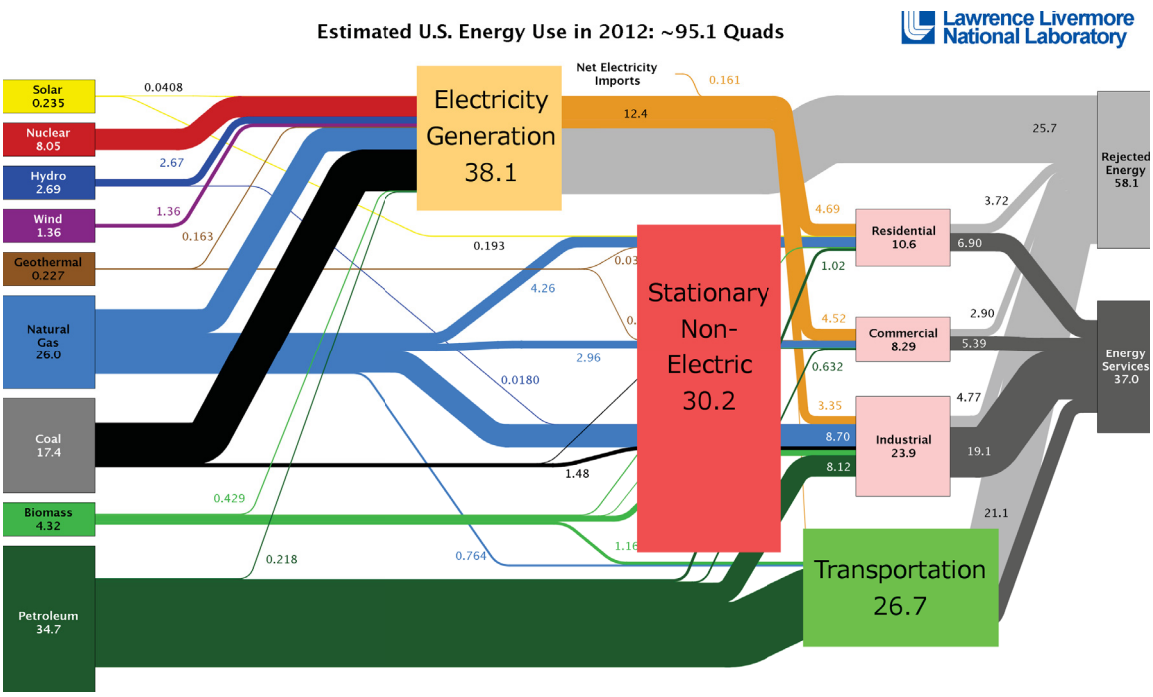


Figure 3: Exemplary US energy flow chart 2012, showing the energy flows and conversions from primary energies (left) to energy services (right). Figure was modified from a figure by Lawrence Livermore National Laboratory/Department of Energy (Lawrence Livermore National Laboratory, 2013).

(IEA, 2012b) and is a highly concentrated sector with relatively few actors. Most importantly, electricity can be produced from a large variety of primary energy types with widely different emission factors, and as an energy carrier, it is not inherently linked to carbon – in contrast to solid and liquid fuels, which partially consist of carbon. The last two points can explain why several studies find that the power sector is the energy sector most suitable for decarbonization (Fawcett et al., 2009; Luderer et al., 2012). Also, from a political economy/transaction-cost point of view, the fact that the power sector is highly centralized and either state-controlled or only recently liberalized can make it more cost-effective and easier to regulate. The EU emissions trading system (EU-ETS), which was instituted in 2005 and puts a cap on certain CO_2 emissions from the 27 EU member states, targets the power sector, large factories in the energy-intensive industries and aviation. The European Commission explains this focus by stating "while emissions trading has the potential to cover many economic sectors and greenhouse gases, the EU ETS focuses on emissions which can be measured, reported and verified with a high level of accuracy" (EC, 2013).

For the power sector, a large number of technology options with low CO_2 emissions exist, although they all have some caveats and should not be seen as "silver bullets". Replacing coal with gas will reduce emissions by about 50%, but a large-scale switch to gas might lead to a lock-in into an infrastructure that is incompatible with the very high emission reductions necessary for limiting warming below 2°C above pre-industrial temperatures. Using biomass instead might lead to the required very low emissions, but the widespread use of biomass can lead to issues of equity, food security, and induced emissions through land use change (Sagar and Kartha, 2007; Fargione et al., 2008; Searchinger et al., 2009; Melillo et al., 2009; Dornburg et al., 2010; Creutzig et al., 2012). Also, biomass is very

versatile and can be used for the production of low-emission liquid fuels and heat, which are heavily demanded by the transport sector and for provision of heat. As the biomass potential is limited, it is therefore not clear whether a cost-efficient energy system will use the limited biomass supply in the power sector. Using CCS in combination with fossil fuels could possibly prevent most of the emissions and allow to use the existing fuel base, but the efforts at scale-up in the last years have been less than promising (von Hirschhausen et al., 2012). Also, doubts about safe long-term storage have led to public opposition. Similar to the situation for biomass, CCS can also be used to produce low-emission liquid fuels, therefore demand from transport and heat sectors will lead to strong competition for secure sequestration sites. Nuclear power has low emissions, but brings both the risk of catastrophic failure as well as the unresolved issues of waste disposal, decommissioning, and proliferation, and thus faces major acceptance issues. Also, uranium supplies for conventional reactors are limited (OECD and IAEA, 2009; Bauer et al., 2012), and past experience with fast breeder reactors has not been encouraging (SCHNEIDER, 2009; Cochran et al., 2010). Hydro power is currently used in many countries of the world, but not much resource potential remains to provide for the scale-up necessary to supply future electricity needs (Horlacher, 2003; Kumar et al., 2011; IEA, 2012a). Wind and solar power resources are huge (Arvizu et al., 2011; Wiser et al., 2011), but unevenly distributed across the globe. More importantly, electricity production from wind and solar is variable, which makes integrating them into the current power system a challenge (see Section 1.4.1). Also, noise and shadowing issues as well as nature conservation concerns have led to public opposition against wind in densely populated regions, suggesting that there is a social limit to the number of wind turbines in one region. Finally, geothermal power is very promising in a few areas of the world where geological conditions are suitable, but for most regions, deep drilling is required, which can bring about small-scale earthquakes and can thus lead to public opposition in densely-populated regions (IEA, 2011; Goldstein et al., 2011).

Electricity is a highly versatile energy carrier whose share in energy system tends to increase strongly as economies develop (Devine, 1983; Ausubel and Marchetti, 1996; Smil, 2000a; Grubler, 2012). Due to its higher value, it currently is mostly used for appliances and other energy services where other fuels are less suited. Under stringent climate mitigation targets, however, the comparatively easier decarbonization of electricity compared to other energy carriers might lead to an expansion of the use of electricity also for heating and mobility (Edmonds et al., 2006; Krey et al., 2014).

Modeling the power sector

From a modeling point of view, the power sector is well suited for representation in an energy-economy model, as consumers have little specific preferences for “different kinds of power”, thus the assumption of rationally optimizing producers and consumers seems well-founded. This condition can be very different for the provision of heat and transport services, where decisions are strongly influenced by individual preferences and lifestyles (especially for specific types of mobility (Anable et al., 2012), transaction costs (e.g., the landlord/tenant dilemma), and other factors (infrastructure dependency of heating and transport systems, timing of renovations) that are not easily accounted for in an aggregated economic modeling framework.

However, complicating issues remain when modeling the power sector, namely that power is an inhomogeneous good in time and space: Demand is varying over time and located at certain points, and generation usually does not fully coincide neither in time nor space, thus additional costs arise to bring the two together (Steiner, 1957; Mohring, 1970; Hausman and Neufeld, 1984; Crew et al., 1995; Hsu, 1997; Stoft, 2002; Bessembinder and Lemmon, 2002; Kirschen, 2003; Green, 2005; Haller, 2012; Ludig, 2013). The fact that demand is variable requires that some power plants only run a few hours per year. This shifts the trade-off between capital intensive power plants like coal or nuclear and low-capital, high fuel cost power plants like gas combustion turbines, leading to a mix of the two types. Modeling the power system with only one energy balance equation requiring that total electricity demand is equal to total electricity production will ignore this trade-off and will, as a consequence, not be able to reproduce the reality. In such a system, different power plants will only compete on LCOE, thus no intermediate or peaking power plants will be built.

To overcome this issue, three main approaches are used in large-scale energy-economy models: time slices[3], load duration curves, and additional flexibility equations (Stoft, 2002; Loulou and Labriet, 2008; Neuhoff et al., 2008; Short et al., 2009; Ludig et al., 2011; Haller, 2012; Sullivan et al., 2013). The first one adds balance equations for several representative times of the year (e.g., high load / medium load / low load) to reproduce the fact that some plants will only run a few hours per year. Load duration curves follow a similar view, but change the basic separation unit from time to capacity. They separate the total capacity into different electricity bands – the "base" band that is always demanded, and one or more "intermediate/peak bands" in which power plants can only produce a limited amount of hours per year. Both approaches directly capture the trade-off between capital and operation costs seen in reality. The third approach is more parameterized – it adds another balance equation requiring that the weighted sum of electricity production must be larger than electricity demand, with different weights attached to different power plants according to their aggregated flexibility. These weights can then be parameterized in such a way that the resulting electricity system is similar to the results from a more detailed bottom-up model that has high temporal resolution and includes detailed ramping constraints and dispatch decisions (Sullivan et al., 2013).

Variable renewable energies

The integration of wind and solar power into the current electricity system poses challenges to both technical system design and market design, as two main characteristics set them apart from thermal power plants: variability and heterogeneity (Grubb, 1991; Skea et al., 2008; Denholm and Hand, 2011; Sims et al., 2011; Mai et al., 2012; Haller, 2012; Mills and Wiser, 2012; Ludig, 2013; Hirth, 2013; Ueckerdt et al., 2013; Edenhofer et al., 2013). Wind and solar power are termed "variable renewable energies" (VRE) due to the temporal variability of the energy resources they rely on. The fluctuations span a wide range of time scales: from minutes (clouds, gusts) to day-night cycles to 3–10 day weather patterns (synoptic) to seasonal and even inter-annual variations. Variability is seen as a

[3] "Peak capacity equations" are a special subgroup of the time slice approach, in which one additional equation requiring that total generation capacity must exceed peak demand plus some reserves – it is essentially a "peak demand time slice" with zero length.

major challenge for the large-scale deployment of VRE, as the current power system design and the behavior of market actors is adapted to dispatchable power plants. A number of flexibility options exist that can facilitate the use of VRE (Sims et al., 2011; Mathiesen et al., 2011), including more flexible generation plants, increased demand response (Stadler, 2008; Roscoe and Ault, 2010; Cappers et al., 2012), increased transmission to regions with different temporal demand and generation profiles (Weigt et al., 2010; Schaber et al., 2012; Haller et al., 2012; Becker et al., 2013; Rodríguez et al., 2014), electricity storage (Drury et al., 2011; Budischak et al., 2013; Steinke et al., 2013), as well as conversion of electricity to other energy vectors whose demand is not temporally correlated or which are easier to store, such as hydrogen or heat (Stadler, 2008; Hedegaard et al., 2012; Arteconi et al., 2012). VRE also suffer from spatial heterogeneity: Wind speed is strongly influenced by geography (mountain ranges, oceans) and local conditions (surface roughness leading to turbulence). For solar power, the latitude is the strongest determinant, but local climate (cloud cover) and human influence (smog) can also influence solar irradiation[4]. If sites with favorable conditions are far from demand centers, the trade-off between transmission costs and lower quality of the renewable resource can be analyzed to determine if it is economical to expand transmission grids in order to achieve higher capacity factors.

Modeling these issues poses a challenge to large-scale energy-economy-models, as they usually have a temporal resolution of 1–5 years and a spatial resolution of country to continent size, which is much too coarse-grained to explicitly include the challenges. Some existing approaches to modeling these challenges are presented in Chapter 3, while a highly stylized custom approach is developed in Chapter 4.

1.4.2 Transport sector

CO_2 emissions from the transport sector make up 22% to total energy-related CO_2 emissions (IEA, 2012b), have experienced substantial growth in the past and are expected to double until 2050 (IEA, 2009). The current transport sector relies almost exclusively on liquid fuels, mostly coming from crude oil (IEA, 2009). Accordingly, it is expected that the transport sector will be particularly difficult to decarbonize (Schäfer and Jacoby, 2006; Barker et al., 2007; Fawcett et al., 2009; Banister et al., 2011; Luderer et al., 2011).

In principle, decarbonization options for the transport sector exist on many different levels (Schafer et al., 2009): Total demand for mobility can be reduced through increased travel costs, improved (urban) infrastructure or changed consumer preferences (Banister et al., 2011; Waisman et al., 2013). Modal shift from travel modes with high carbon intensity such as aviation or private vehicles to ones with lower carbon intensity such as buses, trains or ships will reduce GHG emissions (Cuenot et al., 2012). Within one travel mode, energy demand and thus emissions can be reduced through more efficient vehicles (either through technology or smaller and lighter vehicles), as well as increased load factors.

[4]It should be noted that fossil power is also to some extent geographically heterogeneous: coal power plants are preferably built either close to coal mines or close to rivers or the ocean to allow cheap shipping of coal, and thus not necessarily close to demand centers. If no infrastructure exists, building transmission lines and transporting coal by wire can be cheaper than transporting the coal by rail (Bergerson and Lave, 2005). However, the influence of choosing a suboptimal site for a coal power plant on the price of electricity is lower than the price markup when building a wind farm at a site with very low wind speeds.

Switching to advanced vehicles like plug-in hybrids, battery electric vehicles or fuel cell vehicles not only increases efficiency, but can also open up new paths to low-carbon primary energies like renewable or nuclear energy (Schäfer and Jacoby, 2006; van Vliet et al., 2010; Kyle and Kim, 2011; Bosetti and Longden, 2013). Finally, the Fischer-Tropsch process allows the production of liquid fuels from biomass, coal or natural gas, both with or without CCS (van Vliet et al., 2009; Liu et al., 2011).

However, none of these decarbonization options is expected to be easily deployed. Transport demand has been persistent in the past, and is strongly influenced by urban form and lifestyle, both of which are slow to change. Infrastructure development has been mainly geared towards light-duty vehicles, and a fundamental mind change would be required to achieve modal shift to less carbon-intensive modes. Advanced battery-electric or hydrogen fuel cell vehicles are currently substantially more expensive than regular internal combustion engines, and require the build-up of a comprehensive refueling network – a chicken-and-egg coordination challenge. The extent to which the various mitigation options are applied at the different system levels is discussed in Chapter 5.

Further policies besides pricing carbon can have a substantial influence on mobility demands, and thus CO_2 emission. Cuenot et al. (2012) use the IEA's mobility model to develop a passenger transport scenario in which a variety of measures including strong policy action result in modal shifts towards less energy-intensive modes, leading to a 20% decrease of CO_2 emissions in 2050 compared to their reference scenario without these modal shifts.

1.5 Thesis objective and outline

This thesis aims to improve the understanding of the techno-economic achievability of low stabilization targets, with a focus on the role of variable renewable energies and on the transport sector. It addresses a series of questions, which can be grouped into three categories:

Economic implications of stringent climate targets

What are the economic costs of low stabilization scenarios?
What are the main characteristics and determinants of these mitigation scenarios?
What are the technologies contributing most to emission reductions?
How do the structural patterns of the decarbonization of different sectors compare?

Variable renewable energies

How important are variable renewable energies for decarbonizing the power sector?
How important are system integration costs for the deployment of VRE?
What influences the answers to these questions in different IAMs?

Transport sector decarbonization

How much and through which options can transport emissions be reduced?
How does transport decarbonization compare to the decarbonization of other sectors?

These questions have been addressed in five journal publications, which are reproduced as Chapters 2–6 of this thesis. The publications are based on the results of energy-economy

models, mostly the REMIND model. The author of this thesis significantly contributed to the development and fundamental improvement of REMIND in the process of answering the research questions by

- introducing adjustment costs for more realistic technology deployment paths
- developing more realistic final energy demand projections and calibrating the model with respect to these projections
- developing a transport sector representation with explicit modeling of vehicle stock
- developing simplified storage and grid expansion cost representations
- introducing a new solar technology (concentrating solar power, CSP) and updating parameters for photovoltaics (PV)
- developing a new resource data set for solar power technologies

Chapters 3 and 5 also include results from other energy-economy-models, which were provided by courtesy of the respective modeling teams named in the individual publications in the context of IAM model-comparison projects.

1.5.1 Structure of the thesis

The thesis consists of five self-contained articles either published or under review in peer-reviewed journals. The design of the thesis is presented in Figure 4. Chapters 2 and 6

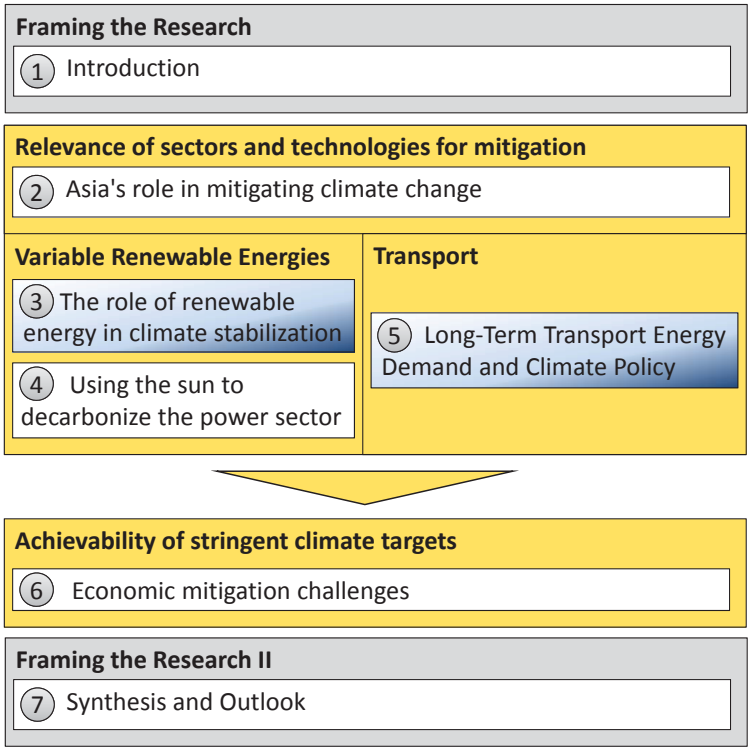


Figure 4: Overview of the thesis structure, with grey circles showing the chapter numbers. Chapters shown with blue shading consist of model comparison studies and include the results of many IAMs.

bracket the research by discussing the general structure of mitigation scenarios developed with the energy-economy-climate model REMIND, and ultimately investigating the economic feasibility of climate mitigation targets at an aggregated level. Two aspects of energy transformation scenarios are then investigated in more detail: Chapters 3 and 4 discuss renewable energies, with a focus on variable renewable energies and how they are represented in energy-economy-models. Chapter 5 turns to the transport sector and analyzes how different IAMs model the decarbonization of transport, and if the different models come to similar results. Chapter 6 finally addresses the fundamental research question and scans a large number of scenarios to map the trade-offs between ambition of climate policy, economic implications, technology availability, and further delay before implementing climate policies. In the following, we provide a brief introduction to each of the chapters:

Chapter 2: Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R

To complement the commonly used metrics "technology deployment" and "technology option values", we develop an innovative and enhanced metric that attributes emission reductions between reference and climate mitigation scenarios to specific technologies. It thereby facilitates discerning technologies and sectors that contribute most to mitigation, pointing out enabling factors as well as possible bottlenecks of the required energy system transformation. We apply this metric to REMIND mitigation scenarios produced for the "Asian Modeling Exercise".

Chapter 3: The role of renewable energy in climate stabilization: results from the EMF27 scenarios

This chapter provides a comprehensive assessment of renewable energy deployment across a large number of energy-economy-emission models. Using several technology-restricted scenarios, we analyze the importance of renewable energies for mitigation, both for electricity and other energy provision. To develop an understanding of the differing results from the various models, we discuss their assumptions about the main drivers of deployment of variable renewable energies, namely technology costs, resource potentials and system integration mechanisms.

Chapter 4: Using the sun to decarbonize the power sector: The economic potential of photovoltaics and concentrating solar power

Motivated by the substantial differences in VRE deployment in the IAMs analyzed in Chapter 3, this chapter focuses in depth on the economic importance of a sub-class of variable renewable energies, namely the solar technologies photovoltaics and concentrating solar power, for the decarbonization of the electricity sector. To do so, we create a full set of updated techno-economic input parameters for these technologies, including investment costs and resource potential. Developing a simplified representation of VRE system integration costs for use in large-scale energy-economy-models, we analyze the importance of these cost markups for technology choice in climate mitigation scenarios.

Finally, we perform a large number of scenario runs to test the robustness of our results towards assumptions about future cost reductions of solar technologies.

Beyond providing policy-relevant findings, this chapter also serves to document the process of developing and augmenting REMIND. Large-scale energy-economy-models are never "finished" – as the world itself changes, as some technologies are further developed while others prove more expensive than expected, as some economies grow while others meet development barriers, these models need to be adapted, refined, improved and checked against actual developments to produce more plausible and therefore more useful future scenarios.

Chapter 5: Long-Term Transport Energy Demand and Climate Policy: Alternative Visions on Transport Decarbonization in Energy Economy Models

Both the results from Chapter 2 as well as previous model comparison studies have pointed to the transport sector as being difficult and late to decarbonize in comparison to the power sector. We therefore perform a model comparison study dedicated to the transport sector: how do different IAMs represent the transport sector, and how similar are their results? We systematically analyze the various mitigation options along the chain of causality, including demand reduction, vehicle choice, energy conversion pathways and carbon capture and sequestration. We discuss differences in timing of decarbonization between the transport sector and the other sectors.

Chapter 6: Economic mitigation challenges: how further delay closes the door for achieving climate targets

In this chapter, we employ a large number of scenarios produced with the augmented REMIND model to comprehensively address the fundamental research question of this thesis, namely the economic achievability of stringent climate mitigation. We simultaneously explore several dimensions of climate policy scenarios, namely the stringency of climate targets, technology availability, as well as different delays before comprehensive climate policy is implemented. We use four policy-relevant metrics to explore economic implications of climate policies, including long-term aggregated costs as well as transitional costs and short-term energy price increases.

References

Abaza, H., Baranzini, A., Jan. 2002. Implementing Sustainable Development: Integrated Assessment and Participatory Decision-making Processes. Edward Elgar Publishing.

Ackerman, F., DeCanio, S. J., Howarth, R. B., Sheeran, K., 2009. Limitations of integrated assessment models of climate change. Climatic Change 95 (3-4), 297–315. http://link.springer.com/article/10.1007/s10584-009-9570-x

Ackerman, F., Munitz, C., May 2012. Climate damages in the FUND model: A disaggregated analysis. Ecological Economics 77, 219–224. http://www.sciencedirect.com/science/article/pii/S0921800912001176

Anable, J., Brand, C., Tran, M., Eyre, N., Feb. 2012. Modelling transport energy demand: A socio-technical approach. Energy Policy 41 (0), 125–138.
http://www.sciencedirect.com/science/article/pii/S030142151000635X

Arrow, K., Cline, W., Maler, K.-G., Munasinghe, M., Squitieri, R., Stiglitz, J., 1996a. Ch4: Intertemporal equity, discounting, and economic efficiency. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Arrow, K., Cropper, M., Gollier, C., Groom, B., Heal, G., Newell, R., Nordhaus, W., Pindyck, R., Pizer, W., Portney, P., Sterner, T., Tol, R. S. J., Weitzman, M., Jul. 2013. Determining benefits and costs for future generations. Science 341 (6144), 349–350, PMID: 23888025.
http://www.sciencemag.org/content/341/6144/349

Arrow, K. J., Cropper, M. L., Eads, G. C., Hahn, R. W., Lave, L. B., Noll, R. G., Portney, P. R., Russell, M., Schmalensee, R., Smith, V. K., Stavins, R. N., Apr. 1996b. Is there a role for benefit-cost analysis in environmental, health, and safety regulation? Science 272 (5259), 221–222, PMID: 8602504.
http://www.sciencemag.org/content/272/5259/221

Arteconi, A., Hewitt, N., Polonara, F., May 2012. State of the art of thermal storage for demand-side management. Applied Energy 93, 371–389.
http://www.sciencedirect.com/science/article/pii/S0306261911008415

Arvizu, D., Balaya, P., Cabeza, L. F., Hollands, K. G. T., Jäger-Waldau, A., Kondo, M., Konseibo, C., Meleshko, V., Stein, W., Tamaura, Y., Xu, H., Zilles, R., 2011. Direct solar energy. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Ausubel, J. H., Marchetti, C., 1996. Elektron: electrical systems in retrospect and prospect. Daedalus 125 (3), 139–169.
http://www.jstor.org/stable/10.2307/20027374

Azar, C., Lindgren, K., Andersson, B. A., Aug. 2003. Global energy scenarios meeting stringent CO2 constraints—cost-effective fuel choices in the transportation sector. Energy Policy 31 (10), 961–976.
http://www.sciencedirect.com/science/article/pii/S0301421502001398

Azar, C., Lindgren, K., Larson, E., Möllersten, K., Jan. 2006. Carbon capture and storage from fossil fuels and biomass – costs and potential role in stabilizing the atmosphere. Climatic Change 74 (1-3), 47–79.
http://link.springer.com/article/10.1007/s10584-005-3484-7

Banister, D., Anderton, K., Bonilla, D., Givoni, M., Schwanen, T., 2011. Transportation and the environment. Annual Review of Environment and Resources 36 (1), 247–270.
http://www.annualreviews.org/doi/abs/10.1146/annurev-environ-032310-112100

Banuri, T., Göran-Mäler, K., Grubb, M., Jacobson, H., Yamin, F., 1996. Ch3: Equity and social considerations. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Banuri, T., Weyant, J., 2001. Ch1: Setting the stage: Climate change and sustainable development. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Barker, T., Bashmakov, I., Alharthi, A., Amann, M., Cifuentes, L., Drexhage, J., Duan, M., Edenhofer, O., Flannery, B., Grubb, T., Hoogwijk, M., Ibitoye, F., Jepma, C., Pizer, W., Yamaji, N., 2007. Ch11: Mitigation from a cross-sectoral perspective. In: Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the IPCC. Cambrigde University Press, Cambridge, United Kingdom and New York, NY, USA.

Barker, T., Serban Scrieciu, S., Sep. 2010. Modeling low climate stabilization with E3MG: towards a 'New economics' approach to simulating energy-environment-economy system dynamics. The Energy Journal 31 (01).
http://www.iaee.org/en/publications/ejarticle.aspx?id=2371

Barker, T., Srivastava, L., 2001. Ch9: Sector costs and ancillary benefits of mitigation. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Bataille, C., Jaccard, M., Nyboer, J., Rivers, N., Sep. 2006. Towards general equilibrium in a technology-rich model with empirically estimated behavioral parameters. The Energy Journal SI2006 (01).
http://www.iaee.org/en/publications/ejarticle.aspx?id=2169

Bauer, N., Brecha, R. J., Luderer, G., Oct. 2012. Economics of nuclear power and climate change mitigation policies. Proceedings of the National Academy of Sciences 109 (42), 16805–16810.
http://www.pnas.org/content/109/42/16805

Becker, S., Rodriguez, R., Andresen, G., Schramm, S., Greiner, M., 2013. Transmission grid extensions during the build-up of a fully renewable pan-european electricity supply. Energy.
http://www.sciencedirect.com/science/article/pii/S0360544213008438

Bergerson, J. A., Lave, L. B., Aug. 2005. Should we transport coal, gas, or electricity: cost, efficiency, and environmental implications. Environmental Science & Technology 39 (16), 5905–5910.
http://dx.doi.org/10.1021/es048981t

Bertram, C., Johnson, N., Luderer, G., Riahi, K., Isaac, M., Eom, J., 2014. Carbon lock-in through capital stock inertia associated with weak near-term climate policies. Technological Forecasting and Social Change.
http://www.sciencedirect.com/science/article/pii/S004016251300259X

Bessembinder, H., Lemmon, M. L., 2002. Equilibrium pricing and optimal hedging in electricity forward markets. The Journal of Finance 57 (3), 1347–1382.
http://onlinelibrary.wiley.com/doi/10.1111/1540-6261.00463/abstract

Bhattacharyya, S. C., Timilsina, G. R., Apr. 2010. Modelling energy demand of developing countries: Are the specific features adequately captured? Energy Policy 38 (4), 1979–1990.
http://www.sciencedirect.com/science/article/pii/S030142150900929X

Böhringer, C., Rutherford, T. F., 2008. Combining bottom-up and top-down. Energy Economics 30 (2), 574–596.
http://www.sciencedirect.com/science/article/pii/S014098830700059X

Blanford, G. J., Rose, S. K., Tavoni, M., Dec. 2012. Baseline projections of energy and emissions in asia. Energy Economics 34, Supplement 3, S284–S292.
http://www.sciencedirect.com/science/article/pii/S0140988312001764

Bosetti, V., Carraro, C., Galeotti, M., Massetti, E., Tavoni, M., Nov. 2006. WITCH - a world induced technical change hybrid model. SSRN eLibrary.
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=948382

Bosetti, V., Longden, T., Jul. 2013. Light duty vehicle transportation and global climate policy: The importance of electric drive vehicles. Energy Policy 58, 209–219.
http://www.sciencedirect.com/science/article/pii/S0301421513001626

Bouwman, A. F., Kram, T., Klein Goldewijk, K., 2006. Integrated modelling of global environmental change, an overview of IMAGE 2.4, netherlands environmental assessment agency. MNP, Bilthoven, The Netherlands.

Brekke, K. A., Johansson-Stenman, O., Jun. 2008. The behavioural economics of climate change. Oxford Review of Economic Policy 24 (2), 280–297.
http://oxrep.oxfordjournals.org/content/24/2/280

Brenkert, A. L., Sands, R. D., Kim, S. H., Pitcher, H. M., 2004. Model Documentation: Second Generation Model. Joint Global Change Research Institute.
http://nsdi.epa.gov/air/pdfs/SGMdocumentation.pdf

Budischak, C., Sewell, D., Thomson, H., Mach, L., Veron, D. E., Kempton, W., Mar. 2013. Cost-minimized combinations of wind power, solar power and electrochemical storage, powering the grid up to 99.9% of the time. Journal of Power Sources 225, 60–74.
http://www.sciencedirect.com/science/article/pii/S0378775312014759

Calvin, K., Clarke, L., Edmonds, J., Eom, J., Hejazi, M., Kim, S., Kyle, G., Link, R., Luckow, P., Patel, P., 2011. GCAM wiki documentation. Tech. rep., Pacific Northwest National Laboratory, Richland, WA.
https://wiki.umd.edu/gcam/

Calvin, K., Clarke, L., Krey, V., Blanford, G., Jiang, K., Kainuma, M., Kriegler, E., Luderer, G., Shukla, P., Dec. 2012a. The role of asia in mitigating climate change: Results from the asia modeling exercise. Energy Economics 34, Supplement 3 (0),

S251–S260.
http://www.sciencedirect.com/science/article/pii/S0140988312002174

Calvin, K., Fawcett, A., Kejun, J., Dec. 2012b. Comparing model results to national climate policy goals: Results from the asia modeling exercise. Energy Economics 34, Supplement 3, S306–S315.
http://www.sciencedirect.com/science/article/pii/S0140988312000527

Cappers, P., Mills, A., Goldman, C., Wiser, R., Eto, J. H., Sep. 2012. An assessment of the role mass market demand response could play in contributing to the management of variable generation integration issues. Energy Policy 48, 420–429.
http://www.sciencedirect.com/science/article/pii/S0301421512004521

Capros, P., 2004. The PRIMES energy system model summary description. Athens (GR): National Technical University of Athens (NTUA).
http://www.e3mlab.ntua.gr/e3mlab/PRIMES%20Manual/PRIMsd.pdf

Capros, P., Paroussos, L., Fragkos, P., Tsani, S., Boitier, B., Wagner, F., Busch, S., Resch, G., Blesl, M., Bollen, J., 2014. Description of models and scenarios used to assess european decarbonisation pathways. Energy Strategy Reviews.
http://www.sciencedirect.com/science/article/pii/S2211467X13001065

Capros, P., Regemorter, D. V., Paroussos, L., Karkatsoulis, P., Fragkiadakis, C., Tsani, S., Charalampidis, I., Revesz, T., 2013. GEM-E3 model documentation. JRC-IPTS Working Paper JRC83177, Institute for Prospective and Technological Studies, Joint Research Centre.
http://ideas.repec.org/p/ipt/iptwpa/jrc83177.html

Cass, D., 1965. Optimum growth in an aggregative model of capital accumulation. The Review of Economic Studies 32 (3), 233–240.
http://www.jstor.org/stable/10.2307/2295827

Chaturvedi, V., Waldhoff, S., Clarke, L., Fujimori, S., Dec. 2012. What are the starting points? evaluating base-year assumptions in the asian modeling exercise. Energy Economics 34, Supplement 3, S261–S271.
http://www.sciencedirect.com/science/article/pii/S0140988312001090

Clarke, L., Krey, V., Weyant, J., Chaturvedi, V., Dec. 2012. Regional energy system variation in global models: Results from the asian modeling exercise scenarios. Energy Economics 34, Supplement 3, S293–S305.
http://www.sciencedirect.com/science/article/pii/S0140988312001624

Clarke, L., Weyant, J., Dec. 2009. Introduction to the EMF 22 special issue on climate change control scenarios. Energy Economics 31, Supplement 2, S63.
http://www.sciencedirect.com/science/article/pii/S0140988309001972

Cochran, T. B., Feiveson, H. A., Patterson, W., Pshakin, G., Ramana, M. V., Schneider, M., Suzuki, T., von Hippel, F., 2010. Fast breeder reactor programs: History and status. International Panel on Fissile Materials Research Report 8.
http://www.fissilematerialsworkinggroup.org/SiteFiles/IPFM_Fast_Breeder_Reactor_Programs_2010.pdf

Cook, J., Nuccitelli, D., Green, S. A., Richardson, M., Winkler, B., Painting, R., Way, R., Jacobs, P., Skuce, A., Jun. 2013. Quantifying the consensus on anthropogenic global warming in the scientific literature. Environmental Research Letters 8 (2), 024024.
http://iopscience.iop.org/1748-9326/8/2/024024

Craig, P. P., Gadgil, A., Koomey, J. G., 2002. WHAT CAN HISTORY TEACH US? a retrospective examination of long-term energy forecasts for the united states*. Annual Review of Energy and the Environment 27 (1), 83–118.
http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.27.122001.083425

Creutzig, F., Popp, A., Plevin, R., Luderer, G., Minx, J., Edenhofer, O., May 2012. Reconciling top-down and bottom-up modelling on future bioenergy deployment. Nature Climate Change 2 (5), 320–327.
http://www.nature.com/nclimate/journal/v2/n5/abs/nclimate1416.html

Crew, M. A., Fernando, C. S., Kleindorfer, P. R., Nov. 1995. The theory of peak-load pricing: A survey. Journal of Regulatory Economics 8 (3), 215–248.
http://link.springer.com/article/10.1007/BF01070807

Criqui, P., Mima, S., Viguier, L., Oct. 1999. Marginal abatement costs of CO2 emission reductions, geographical flexibility and concrete ceilings: an assessment using the POLES model. Energy Policy 27 (10), 585–601.
http://www.sciencedirect.com/science/article/pii/S0301421599000518

Cuenot, F., Fulton, L., Staub, J., Feb. 2012. The prospect for modal shifts in passenger transport worldwide and impacts on energy use and CO2. Energy Policy 41 (0), 98–106.
http://www.sciencedirect.com/science/article/pii/S0301421510005471

Dasgupta, P., Dec. 2008. Discounting climate change. Journal of Risk and Uncertainty 37 (2-3), 141–169.
http://link.springer.com/article/10.1007/s11166-008-9049-6

DeCarolis, J. F., Mar. 2011. Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. Energy Economics 33 (2), 145–152.
http://www.sciencedirect.com/science/article/pii/S0140988310000721

DeCarolis, J. F., Hunter, K., Sreepathi, S., Nov. 2012. The case for repeatable analysis with energy economy optimization models. Energy Economics 34 (6), 1845–1853.
http://www.sciencedirect.com/science/article/pii/S0140988312001405

Denholm, P., Hand, M., Mar. 2011. Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. Energy Policy 39 (3), 1817–1830.
http://www.sciencedirect.com/science/article/pii/S0301421511000292

Derr, N. S. T., Patrick, Jan. 2009. Contra epstein, good explanations predict.
http://jasss.soc.surrey.ac.uk/12/1/9.html

Devine, W. D., 1983. From shafts to wires: Historical perspective on electrification. The Journal of Economic History 43 (02), 347–372.

Dixon, P. B., Jorgenson, D., 2012. Handbook of Computable General Equilibrium Modeling. Elsevier Science.

Dornburg, V., Vuuren, D. v., Ven, G. v. d., Langeveld, H., Meeusen, M., Banse, M., Oorschot, M. v., Ros, J., Born, G. J. v. d., Aiking, H., Londo, M., Mozaffarian, H., Verweij, P., Lysen, E., Faaij, A., Mar. 2010. Bioenergy revisited: Key factors in global potentials of bioenergy. Energy & Environmental Science 3 (3), 258–267.
http://pubs.rsc.org/en/content/articlelanding/2010/ee/b922422j

Drury, E., Denholm, P., Sioshansi, R., Aug. 2011. The value of compressed air energy storage in energy and reserve markets. Energy 36 (8), 4959–4973.
http://www.sciencedirect.com/science/article/pii/S0360544211003665

EC, 2013. Fact sheet: The EU emissions trading system (EU ETS). Tech. rep., European Commission Publications Office.
http://ec.europa.eu/clima/publications/docs/factsheet_ets_en.pdf

Edenhofer, O., Bauer, N., Kriegler, E., Aug. 2005. The impact of technological change on climate protection and welfare: Insights from the model MIND. Ecological Economics 54 (2–3), 277–292.
http://www.sciencedirect.com/science/article/pii/S0921800905000376

Edenhofer, O., Carraro, C., Hourcade, J.-C., Sep. 2012. On the economics of decarbonization in an imperfect world. Climatic Change 114 (1), 1–8.
http://link.springer.com/article/10.1007/s10584-012-0549-7

Edenhofer, O., Hirth, L., Knopf, B., Pahle, M., Schlömer, S., Schmid, E., Ueckerdt, F., Dec. 2013. On the economics of renewable energy sources. Energy Economics 40, Supplement 1, S12–S23.
http://www.sciencedirect.com/science/article/pii/S0140988313002107

Edenhofer, O., Knopf, B., Barker, T., Baumstark, L., Bellevrat, E., Chateau, B., Criqui, P., Isaac, M., Kitous, A., Kypreos, S., 2010a. The economics of low stabilization: model comparison of mitigation strategies and costs. The Energy Journal 31 (1), 11–48.
http://lepii.upmf-grenoble.fr/IMG/pdf/PC_article-energy-journal_vol31.pdf

Edenhofer, O., Knopf, B., Leimbach, M., Bauer, N., 2010b. ADAM's modeling comparison project-intentions and prospects. The Energy Journal 31 (Special Issue).
http://econpapers.repec.org/RePEc:aen:journl:2010se1-low-stabilization-a01

Edenhofer, O., Lessmann, K., Kemfert, C., Grubb, M., Köhler, J., 2006. Induced technological change: Exploring its implications for the economics of atmospheric stabilization: Synthesis report from the innovation modeling comparison project. The Energy Journal 27 (special issue 1), 57–107.
http://www.pik-potsdam.de/members/edenh/publications-1/edenhoferlessmannkemfertgrubbkoehler.pdf

Edmonds, J., Luckow, P., Calvin, K., Wise, M., Dooley, J., Kyle, P., Kim, S. H., Patel, P., Clarke, L., May 2013. Can radiative forcing be limited to 2.6 wm2 without negative emissions from bioenergy AND CO2 capture and storage? Climatic Change 118 (1), 29–43.
http://link.springer.com/article/10.1007/s10584-012-0678-z

Edmonds, J., Wilson, T., Wise, M., Weyant, J., 2006. Electrification of the economy and CO2 emissions mitigation. Environmental economics and policy studies 7 (3), 175–203.
http://cat.inist.fr/?aModele=afficheN&cpsidt=17776818

Epstein, J. M., Oct. 2008. Why model?
http://jasss.soc.surrey.ac.uk/11/4/12.html

Fargione, J., Hill, J., Tilman, D., Polasky, S., Hawthorne, P., Feb. 2008. Land clearing and the biofuel carbon debt. Science 319 (5867), 1235–1238, PMID: 18258862.
http://www.sciencemag.org/content/319/5867/1235

Fawcett, A. A., Calvin, K. V., de la Chesnaye, F. C., Reilly, J. M., Weyant, J. P., Dec. 2009. Overview of EMF 22 U.S. transition scenarios. Energy Economics 31, Supplement 2 (0), S198–S211.
http://www.sciencedirect.com/science/article/pii/S0140988309001984

Fisher, B., Nakicenovic, N., Alfsen, K., Corfee Morlot, J., de la Chesnaye, F., Hourcade, J.-C., Kainuma, M., La Rovere, E., Matysek, A., Rana, A., Riahi, K., Richels, R., Rose, S., van Vurren, D., Warren, R., 2007. Ch3: Issues related to mitigation in the long term context. In: Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the IPCC. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Fisher-Vanden, K., Schu, K., Sue Wing, I., Calvin, K., Dec. 2012. Decomposing the impact of alternative technology sets on future carbon emissions growth. Energy Economics 34, Supplement 3, S359–S365.
http://www.sciencedirect.com/science/article/pii/S014098831200165X

Ghersi, F., Hourcade, J.-C., Sep. 2006. Macroeconomic consistency issues in e3 modeling: The continued fable of the elephant and the rabbit. The Energy Journal SI2006 (01).
http://www.iaee.org/en/publications/ejarticle.aspx?id=2167

Gillingham, K., Newell, R. G., Pizer, W. A., Nov. 2008. Modeling endogenous technological change for climate policy analysis. Energy Economics 30 (6), 2734–2753.
http://www.sciencedirect.com/science/article/pii/S0140988308000443

Goettle, R. J., Ho, M. S., Jorgenson, D. W., Slesnick, D. T., Wilcoxen, P. J., EP-W, E. C., 2007. IGEM, an inter-temporal general equilibrium model of the US economy with emphasis on growth, energy and the environment. Model documentation in support of ongoing policy analysis for the US Environmental Protection Agency, EPA Contract No. EP-W-05-035.

http://gking.harvard.edu/files/jorgenson/files/igem_documentation-1.pdf

Goldstein, B., Hiriart, G., Bertani, R., Bromley, C., Gutiérrez-Negrín, L., Huenges, E., Muraoka, H., Ragnarsson, A., Tester, J., Zui, V., 2011. Geothermal energy. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Green, R., Mar. 2005. Electricity and markets. Oxford Review of Economic Policy 21 (1), 67–87.
http://oxrep.oxfordjournals.org/content/21/1/67

Grubb, M., Sep. 1991. The integration of renewable electricity sources. Energy Policy 19 (7), 670–688.
http://www.sciencedirect.com/science/article/pii/0301421591901003

Grubb, M., Köhler, J., Anderson, D., 2002. INDUCED TECHNICAL CHANGE IN ENERGY AND ENVIRONMENTAL MODELING: analytic approaches and policy implications. Annual Review of Energy and the Environment 27 (1), 271–308.
http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.27.122001.083408

Grubler, A., Nov. 2012. Energy transitions research: Insights and cautionary tales. Energy Policy 50, 8–16.
http://www.sciencedirect.com/science/article/pii/S0301421512002054

Gupta, S., Tirpak, D., Burger, N., Gupta, J., Höhne, N., Boncheva, A., Kanoan, M., Kolstad, C., Kruger, J., Michaelowa, A., Murase, S., Pershing, J., Saijo, T., Sari, W., 2007. Ch13: Policies, instruments and co-operative arrangements. In: Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the IPCC. Cambrigde University Press, Cambridge, United Kingdom and New York, NY, USA.

Haller, M., 2012. CO2 mitigation and power system integration of fluctuating renewable energy sources: A multi-scale modeling approach. Ph.D. thesis, Technische Universität Berlin, Berlin, Germany.
http://opus4.kobv.de/opus4-tuberlin/frontdoor/index/index/docId/3254

Haller, M., Ludig, S., Bauer, N., Aug. 2012. Decarbonization scenarios for the EU and MENA power system: Considering spatial distribution and short term dynamics of renewable generation. Energy Policy 47, 282–290.
http://www.sciencedirect.com/science/article/pii/S0301421512003746

Halsnaes, K., Shukla, P., Ahuja, D., Akumu, G., Beale, R., Edmonds, J., Gollier, C., Grübler, A., Ha Duong, M., Markandya, A., McFarland, M., Nikitina, E., Sugiyama, T., Villavicencio, A., 2007. Ch2: Framing issues. In: Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L. (Eds.), Climate Change 2007: Mitigation. Contribution of Working

Group III to the Fourth Assessment report of the IPCC. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Hausman, W. J., Neufeld, J. L., 1984. Time-of-day pricing in the US electric power industry at the turn of the century. The RAND Journal of Economics, 116–126.
http://www.jstor.org/stable/10.2307/3003674

Heaps, C., 2008. An introduction to LEAP. Stockholm Environment Institute.
http://www.leap2000.org/documents/LEAPIntro.pdf

Hedegaard, K., Mathiesen, B. V., Lund, H., Heiselberg, P., Nov. 2012. Wind power integration using individual heat pumps – analysis of different heat storage options. Energy 47 (1), 284–293.
http://www.sciencedirect.com/science/article/pii/S0360544212007086

Hedenus, F., Johansson, D., Lindgren, K., 2013. A critical assessment of energy-economy-climate models for policy analysis. Journal of Applied Economics and Business Research 3 (2), 118–132.
http://www.aebrjournal.org/uploads/6/6/2/2/6622240/joaebrjune2013_118_132.pdf

Hertel, T. W., 1999. Global trade analysis: modeling and applications. Cambridge university press.

Hirth, L., Jul. 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Economics 38, 218–236.
http://www.sciencedirect.com/science/article/pii/S0140988313000285

Horlacher, H. B., 2003. Globale potentiale der wasserkraft. externe expertise für das WBGU-Hauptgutachten 2003 "Welt im wandel: Energiewende zur nachhaltigkeit". Tech. rep.

Horne, M., Jaccard, M., Tiedemann, K., 2005. Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions. Energy Economics 27 (1), 59–77.
http://www.sciencedirect.com/science/article/pii/S0140988304000982

Hourcade, J. C., Halsnaes, K., Jaccard, M., Montgomery, W., Richels, R., Robinson, J., Shukla, P., Sturm, P., 1996a. Ch9: A review of mitigation cost studies. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Hourcade, J. C., Jaccard, M., Bataille, C., Ghersi, F., Oct. 2006. Hybrid modeling: New answers to old challenges. The Energy Journal 2 (Special issue), 1–12.
http://halshs.archives-ouvertes.fr/halshs-00471234

Hourcade, J. C., Richels, R., Robinson, J., 1996b. Ch8: Estimating the costs of mitigating greenhouse gases. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Hourcade, J.-C., Shukla, P., 2001. Ch8: Global, regional, and national costs and ancillary benefits of mitigation. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Howells, M., Rogner, H., Strachan, N., Heaps, C., Huntington, H., Kypreos, S., Hughes, A., Silveira, S., DeCarolis, J., Bazillian, M., Roehrl, A., Oct. 2011. OSeMOSYS: the open source energy modeling system: An introduction to its ethos, structure and development. Energy Policy 39 (10), 5850–5870.
http://www.sciencedirect.com/science/article/pii/S0301421511004897

Hsu, M., Sep. 1997. An introduction to the pricing of electric power transmission. Utilities Policy 6 (3), 257–270.
http://www.sciencedirect.com/science/article/pii/S0957178797000131

IEA, 2009. Transport, Energy and CO2: Moving Towards Sustainability. OECD Publishing, Paris, France.

IEA, 2011. Technology roadmap: Geothermal heat and power. Tech. rep., IEA.
http://www.iea.org/publications/freepublications/publication/name,3988,en.html

IEA, 2012a. Technology roadmaps: Hydropower. Tech. rep., IEA.
www.iea.org/publications/freepublications/publication/2012_Hydropower_Roadmap.pdf

IEA, 2012b. WEO - World Energy Outlook 2012. International Energy Agency, Paris.

IPCC, 2007. Climate change 2007: AR4 synthesis report. Tech. rep., Intergovernmental Panel on Climate Change.
http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf

IPCC, 2013. Summary for policymakers. In: Stocker, T. F., Qin, D., Plattner, G. K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,.

Jaeger, C. C., Paroussos, L., Mangalagiu, D., Kupers, R., Mandel, A., Tàbara, J. D., Botta, N., Fürst, S., Henning, E., Ionescu, C., 2011. A new growth path for europe. Generating Prosperity and Jobs in the Low-Carbon Economy. Synthesis Report PIK, University of Oxford, ICCS, Université Paris 1.
http://www.euractiv.com/sites/all/euractiv/files/m30_Synthesis_0.pdf

Janetos, A., 2009. Science challenges and future directions: Climate change integrated assessment research. Tech. Rep. PNNL-18417, U.S. DOE, Office of Science.
http://www.pnl.gov/atmospheric/docs/climate_change_assessment.pdf

Kainuma, M., Matsuoka, Y., Morita, T., 2003. Climate policy assessment: Asia-Pacific integrated modeling. Springer.

Kaufman, N., Feb. 2012. The bias of integrated assessment models that ignore climate catastrophes. Climatic Change 110 (3-4), 575–595.
http://link.springer.com/article/10.1007/s10584-011-0140-7

Keepin, B., Wynne, B., Dec. 1984. Technical analysis of IIASA energy scenarios. Nature 312 (5996), 691–695.
http://www.nature.com/nature/journal/v312/n5996/abs/312691a0.html

Kesicki, F., Strachan, N., Dec. 2011. Marginal abatement cost (MAC) curves: confronting theory and practice. Environmental Science & Policy 14 (8), 1195–1204.
http://www.sciencedirect.com/science/article/pii/S1462901111001377

Kim, S. H., Edmonds, J., Lurz, J., Smith, S., Wise, M., 2006. The object-oriented energy climate technology systems (ObjECTS) framework and hybrid modeling of transportation in the MiniCAM long-term, global integrated assessment model. The Energy Journal, 63–91.

Kirschen, D. S., 2003. Demand-side view of electricity markets. Power Systems, IEEE Transactions on 18 (2), 520–527.
http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1198281

Kitous, A., Criqui, P., Bellevrat, E., Chateau, B., 2010. Transformation patterns of the worldwide energy system–scenarios for the century with the POLES model. Energy Journal 31 (Special Issue 1 on The Economics of Low Stabilization), 57–90.
http://edden.upmf-grenoble.fr/IMG/pdf/AK-PC-EB-PB_transformation_energyJournal_vol31.pdf

Klein, D., Luderer, G., Kriegler, E., Strefler, J., Bauer, N., Leimbach, M., Popp, A., Dietrich, J. P., Humpenöder, F., Lotze-Campen, H., Edenhofer, O., 2014. The value of bioenergy in low stabilization scenarios: an assessment using REMIND-MAgPIE. Climatic Change, 1–14.
http://link.springer.com/article/10.1007/s10584-013-0940-z

Knopf, B., Edenhofer, O., Flachsland, C., Kok, M. T., Lotze-Campen, H., Luderer, G., Popp, A., van Vuuren, D. P., 2010. Managing the low-carbon Transition—From model results to policies. The Energy Journal 31 (special issue 1), 223–245.
ftp://ftp.elet.polimi.it/users/Marino.Gatto/ASPCourse2010/PolyGame/Knopf_Policy_Energyjournal2010.pdf

Kohler, J., Barker, T., Anderson, D., Pan, H., Sep. 2006. Combining energy technology dynamics and macroeconometrics: The E3MG model. The Energy Journal SI2006 (01).
http://www.iaee.org/en/publications/ejarticle.aspx?id=2170

Koopmans, T. C., 1963. On the concept of optimal economic growth. Cowles Foundation Discussion Paper 163, Cowles Foundation for Research in Economics, Yale University.
http://econpapers.repec.org/paper/cwlcwldpp/163.htm

Krey, V., Luderer, G., Clarke, L., Kriegler, E., 2014. Getting from here to there – energy technology transformation pathways in the EMF27 scenarios. Climatic Change, 1–14.
http://link.springer.com/article/10.1007/s10584-013-0947-5

Krey, V., Riahi, K., Dec. 2009. Implications of delayed participation and technology failure for the feasibility, costs, and likelihood of staying below temperature targets—Greenhouse gas mitigation scenarios for the 21st century. Energy Economics 31, Supplement 2, S94–S106.
http://www.sciencedirect.com/science/article/pii/S0140988309001170

Kriegler, E., Weyant, J. P., Blanford, G. J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S. K., Tavoni, M., Vuuren, D. P. v., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change, 1–15.
http://link.springer.com/article/10.1007/s10584-013-0953-7

Kumar, A., Schei, T., Ahenkorah, A., Rodriguez, R. C., Devernay, J.-M., Freitas, M., Hall, D., Killingtveit, n., Liu, Z., 2011. Hydropower. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Kydes, A. S., Shaw, S. H., McDonald, D. F., Feb. 1995. Beyond the horizon: Recent directions in long-term energy modeling. Energy 20 (2), 131–149.
http://www.sciencedirect.com/science/article/pii/036054429400060G

Kyle, P., Kim, S. H., May 2011. Long-term implications of alternative light-duty vehicle technologies for global greenhouse gas emissions and primary energy demands. Energy Policy 39 (5), 3012–3024.
http://www.sciencedirect.com/science/article/pii/S0301421511001960

Lawrence Livermore National Laboratory, 2013. US energy flow charts.
https://flowcharts.llnl.gov/

Layard, R., Glaister, S., Jun. 1994. Cost-Benefit Analysis. Cambridge University Press.

Leimbach, M., Bauer, N., Baumstark, L., Edenhofer, O., Jun. 2010. Mitigation costs in a globalized world: Climate policy analysis with REMIND-R. Environmental Modeling & Assessment 15 (3), 155–173.
http://link.springer.com/article/10.1007/s10666-009-9204-8

Lejour, A., Veenendaal, P., Verweij, G., van Leeuwen, N., 2006. WorldScan; a model for international economic policy analysis. Tech. rep., CPB Netherlands Bureau for Economic Policy Analysis.
http://ideas.repec.org/p/cpb/docmnt/111.html

Lenton, T. M., Held, H., Kriegler, E., Hall, J. W., Lucht, W., Rahmstorf, S., Schellnhuber, H. J., Feb. 2008. Tipping elements in the earth's climate system. Proceedings of the National Academy of Sciences 105 (6), 1786–1793, PMID: 18258748.
http://www.pnas.org/content/105/6/1786

Leuthold, F. U., Weigt, H., Hirschhausen, C. v., Mar. 2012. A large-scale spatial optimization model of the european electricity market. Networks and Spatial Economics 12 (1),

75–107.
http://link.springer.com/article/10.1007/s11067-010-9148-1

Liu, G., Larson, E. D., Williams, R. H., Kreutz, T. G., Guo, X., Jan. 2011. Making FischerTropsch fuels and electricity from coal and biomass: Performance and cost analysis. Energy & Fuels 25 (1), 415–437.
http://dx.doi.org/10.1021/ef101184e

Loulou, R., Goldstein, G., Noble, K., 2004. Documentation for the MARKAL family of models. Energy Technology Systems Analysis Programme, 65–73.
http://www.eprc.re.kr/upload_dir/board/996338814c4ce3d49fd7c.pdf

Loulou, R., Labriet, M., 2008. ETSAP-TIAM: the TIMES integrated assessment model part i: Model structure. Computational Management Science 5 (1-2), 7–40.
http://link.springer.com/article/10.1007/s10287-007-0046-z

Luderer, G., Bosetti, V., Jakob, M., Leimbach, M., Steckel, J., Waisman, H., Edenhofer, O., 2011. The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison. Climatic Change, 1–29.
http://www.springerlink.com/content/g04377m307g03725/abstract/

Luderer, G., Leimbach, M., Bauer, N., Aboumahboub, T., Curras, T. A., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Mouratiadou, I., Pietzcker, R., Piontek, F., Roming, N., Schultes, A., Schwanitz, V. J., Strefler, J., Aug. 2013a. Description of the REMIND model (version 1.5). SSRN Scholarly Paper ID 2312844, Social Science Research Network, Rochester, NY.
http://papers.ssrn.com/abstract=2312844

Luderer, G., Pietzcker, R. C., Bertram, C., Kriegler, E., Meinshausen, M., Edenhofer, O., Sep. 2013b. Economic mitigation challenges: how further delay closes the door for achieving climate targets. Environmental Research Letters 8 (3), 034033.
http://iopscience.iop.org/1748-9326/8/3/034033

Luderer, G., Pietzcker, R. C., Kriegler, E., Haller, M., Bauer, N., 2012. Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R. Energy Economics 34, Supplement 3, S378–S390.
http://www.sciencedirect.com/science/article/pii/S0140988312001661

Ludig, S., 2013. Renewable energy and CCS in german and european power sector decarbonization scenarios. Ph.D. thesis, Technische Universität Berlin, Berlin, Germany.
http://opus4.kobv.de/opus4-tuberlin/frontdoor/index/index/docId/4372

Ludig, S., Haller, M., Schmid, E., Bauer, N., Nov. 2011. Fluctuating renewables in a long-term climate change mitigation strategy. Energy 36 (11), 6674–6685.
http://www.sciencedirect.com/science/article/pii/S0360544211005512

Mai, T., Sandor, D., Wiser, R., Schneider, T., 2012. Renewable electricity futures study. executive summary. Tech. rep., National Renewable Energy Laboratory (NREL), Golden, CO.
http://www.osti.gov/bridge/product.biblio.jsp?osti_id=1063076

Manne, A., Mendelsohn, R., Richels, R., Jan. 1995. MERGE: a model for evaluating regional and global effects of GHG reduction policies. Energy Policy 23 (1), 17–34.
http://www.sciencedirect.com/science/article/pii/030142159590763W

Manne, A. S., Richels, R. G., 2005. MERGE: an integrated assessment model for global climate change. In: Energy and Environment. Springer, p. 175–189.
http://link.springer.com/content/pdf/10.1007/0-387-25352-1_7.pdf

Manne, A. S., Rutherford, T. F., Jan. 1994. International trade in oil, gas and carbon emission rights: An intertemporal general equilibrium model. The Energy Journal 15 (1).
http://www.iaee.org/en/publications/ejarticle.aspx?id=1146

Markandya, A., Halsnaes, K., 2001. Ch7: Costing methodologies. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Mathiesen, B. V., Lund, H., Karlsson, K., Feb. 2011. 100% renewable energy systems, climate mitigation and economic growth. Applied Energy 88 (2), 488–501.
http://www.sciencedirect.com/science/article/pii/S0306261910000644

Mathiesen, L., Jan. 1985. Computation of economic equilibria by a sequence of linear complementarity problems. In: Manne, A. S. (Ed.), Economic Equilibrium: Model Formulation and Solution. No. 23 in Mathematical Programming Studies. Springer Berlin Heidelberg, pp. 144–162.
http://link.springer.com/chapter/10.1007/BFb0121030

Matthews, H. D., Caldeira, K., Feb. 2008. Stabilizing climate requires near-zero emissions. Geophysical Research Letters 35, L04705.
http://www.agu.org/pubs/crossref/2008/2007GL032388.shtml

Matthews, H. D., Gillett, N. P., Stott, P. A., Zickfeld, K., Jun. 2009. The proportionality of global warming to cumulative carbon emissions. Nature 459 (7248), 829–832.
http://www.nature.com/nature/journal/v459/n7248/full/nature08047.html

Matthews, H. D., Solomon, S., Apr. 2013. Irreversible does not mean unavoidable. Science 340 (6131), 438–439, PMID: 23539182.
http://www.sciencemag.org/content/340/6131/438

Maussner, A., Klump, R., 1996. Wachstumstheorie. Springer DE, Germany.

McFarland, J., Reilly, J., Herzog, H., Jul. 2004. Representing energy technologies in top-down economic models using bottom-up information. Energy Economics 26 (4), 685–707.
http://www.sciencedirect.com/science/article/pii/S0140988304000374

McKibbin, W. J., Wilcoxen, P. J., 1999. The theoretical and empirical structure of the g-cubed model. Economic modelling 16 (1), 123–148.
http://www.sciencedirect.com/science/article/pii/S0264999398000352

Meadows, D. H., Meadows, D. H., Randers, J., Behrens III, W. W., 1972. The Limits to Growth: A Report to The Club of Rome (1972). Universe Books, New York.
http://www.ask-force.org/web/Global-Warming/Meadows-Limits-to-Growth-Short-1972.pdf

Meinshausen, M., Meinshausen, N., Hare, W., Raper, S. C. B., Frieler, K., Knutti, R., Frame, D. J., Allen, M. R., Apr. 2009. Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458 (7242), 1158–1162.
http://www.nature.com/nature/journal/v458/n7242/full/nature08017.html

Melillo, J. M., Reilly, J. M., Kicklighter, D. W., Gurgel, A. C., Cronin, T. W., Paltsev, S., Felzer, B. S., Wang, X., Sokolov, A. P., Schlosser, C. A., Dec. 2009. Indirect emissions from biofuels: How important? Science 326 (5958), 1397–1399, PMID: 19933101.
http://www.sciencemag.org/content/326/5958/1397

Messner, S., Schrattenholzer, L., Mar. 2000. MESSAGE–MACRO: linking an energy supply model with a macroeconomic module and solving it iteratively. Energy 25 (3), 267–282.
http://www.sciencedirect.com/science/article/pii/S0360544299000638

Mills, A., Wiser, R., 2012. Changes in the economic value of variable generation at high penetration levels: A pilot case study of california. Tech. rep., Lawrence Berkeley National Laboratory.
http://escholarship.org/uc/item/2g7677hn

Mishan, E. J., Quah, E., 2007. Cost-benefit analysis. Routledge.

Mohring, H., Sep. 1970. The peak load problem with increasing returns and pricing constraints. The American Economic Review 60 (4), 693–705.
http://www.jstor.org/stable/1818412

Morgan, M. G., Keith, D. W., 2008. Improving the way we think about projecting future energy use and emissions of carbon dioxide. Climatic Change 90 (3), 189–215.
http://link.springer.com/article/10.1007/s10584-008-9458-1

Morita, T., Robinson, J., 2001. Ch2: Greenhouse gas emission mitigation scenarios and implications. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Morris, J., Paltsev, S., Reilly, J., Aug. 2012. Marginal abatement costs and marginal welfare costs for greenhouse gas emissions reductions: Results from the EPPA model. Environmental Modeling & Assessment 17 (4), 325–336.
http://link.springer.com/article/10.1007/s10666-011-9298-7

Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., Wilbanks, T. J., Feb. 2010. The next generation of scenarios for climate change

research and assessment. Nature 463 (7282), 747–756.
http://www.nature.com/nature/journal/v463/n7282//full/nature08823.html

Munasinghe, M., Meier, P., Hoel, M., Hong, S., Aaheim, A., 1996. Ch5: Applicability of techniques of cost-benefit analysis to climate change. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Nakata, T., 2004. Energy-economic models and the environment. Progress in Energy and Combustion Science 30 (4), 417–475.
http://www.sciencedirect.com/science/article/pii/S0360128504000140

Nakicenovic, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T. Y., Kram, T., 2000. Special report on emissions scenarios (SRES): a special report of working group III of the intergovernmental panel on climate change. Tech. rep., Pacific Northwest National Laboratory, Richland, WA (US), Environmental Molecular Sciences Laboratory (US).
http://www.osti.gov/energycitations/product.biblio.jsp?osti_id=15009867

Negishi, T., 1972. General equilibrium theory and international trade. North-Holland Publishing Company Amsterdam, London.
http://library.wur.nl/WebQuery/clc/199209

Neuhoff, K., Ehrenmann, A., Butler, L., Cust, J., Hoexter, H., Keats, K., Kreczko, A., Sinden, G., Jul. 2008. Space and time: Wind in an investment planning model. Energy Economics 30 (4), 1990–2008.
http://www.sciencedirect.com/science/article/pii/S0140988307000904

Nordhaus, W. D., Mar. 1993. Rolling the 'DICE': an optimal transition path for controlling greenhouse gases. Resource and Energy Economics 15 (1), 27–50.
http://www.sciencedirect.com/science/article/pii/092876559390017O

Nordhaus, W. D., 2007. A review of the" stern review on the economics of climate change". Journal of Economic Literature, 686–702.
http://www.jstor.org/stable/10.2307/27646843

Nordhaus, W. D., Boyer, J., 2000. Warming the World: Economic Models of Global Warming. MIT Press.

OECD, IAEA, 2009. Uranium 2009: Resources, Production and Demand. Organisation for Economic Co-operation and Development, Paris.
http://www.oecd-ilibrary.org/content/book/uranium-2009-en

Paltsev, S., Reilly, J. M., Jacoby, H. D., Eckaus, R. S., McFarland, J. R., Sarofim, M. C., Asadoorian, M. O., Babiker, M. H., 2005. The MIT emissions prediction and policy analysis (EPPA) model: version 4. Tech. rep., MIT Joint Program on the Science and Policy of Global Change.
http://dspace.mit.edu/handle/1721.1/29790

Pearce, D., Cline, W., Achanta, A., Fankhauser, S., Pachauri, R., Tol, R. S. J., Vellinga, P., 1996. Ch6: The social costs of climate change: Greenhouse damage and the benefits of control. In: Bruce, J. P., Yi, H., Haites, E. F. (Eds.), Climate change 1995: Economic and social dimensions of climate change: Contribution of Working Group III to the second assessment report of the IPCC. Vol. 3. Cambridge University Press.

Peck, S. C., Teisberg, T. J., Apr. 1995. International CO2 emissions control: An analysis using CETA. Energy Policy 23 (4–5), 297–308.
http://www.sciencedirect.com/science/article/pii/0301421595901562

Popp, A., Lotze-Campen, H., Bodirsky, B., Aug. 2010. Food consumption, diet shifts and associated non-CO2 greenhouse gases from agricultural production. Global Environmental Change 20 (3), 451–462.
http://www.sciencedirect.com/science/article/pii/S0959378010000075

Rabl, A., Jun. 1996. Discounting of long-term costs: What would future generations prefer us to do? Ecological Economics 17 (3), 137–145.
http://www.sciencedirect.com/science/article/pii/S0921800996800024

Ramsey, F. P., Dec. 1928. A mathematical theory of saving. The Economic Journal 38 (152), 543–559.
http://www.jstor.org/stable/2224098

Risbey, J., Sluijs, J. v. d., Kloprogge, P., Ravetz, J., Funtowicz, S., Quintana, S. C., Mar. 2005. Application of a checklist for quality assistance in environmental modelling to an energy model. Environmental Modeling & Assessment 10 (1), 63–79.
http://link.springer.com/article/10.1007/s10666-004-4267-z

Rodríguez, R. A., Becker, S., Andresen, G. B., Heide, D., Greiner, M., Mar. 2014. Transmission needs across a fully renewable european power system. Renewable Energy 63, 467–476.
http://www.sciencedirect.com/science/article/pii/S0960148113005351

Roemer, J. E., Mar. 2011. The ethics of intertemporal distribution in a warming planet. Environmental and Resource Economics 48 (3), 363–390.
http://link.springer.com/article/10.1007/s10640-010-9414-1

Rogelj, J., Hare, W., Lowe, J., van Vuuren, D. P., Riahi, K., Matthews, B., Hanaoka, T., Jiang, K., Meinshausen, M., Nov. 2011. Emission pathways consistent with a 2°C global temperature limit. Nature Climate Change 1 (8), 413–418.
http://www.nature.com/nclimate/journal/v1/n8/full/nclimate1258.html

Roscoe, A., Ault, G., 2010. Supporting high penetrations of renewable generation via implementation of real-time electricity pricing and demand response. IET Renewable Power Generation 4 (4), 369.
http://digital-library.theiet.org/content/journals/10.1049/iet-rpg.2009.0212

Sagar, A. D., Kartha, S., 2007. Bioenergy and sustainable development? Annual Review of Environment and Resources 32 (1), 131–167.

http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.32.062706.132042

Sanstad, A. H., Greening, L. A., Mar. 1998. Economic models for climate policy analysis: A critical discussion. Environmental Modeling & Assessment 3 (1-2), 3–18. http://link.springer.com/article/10.1023/A%3A1019002620369

Schaber, K., Steinke, F., Hamacher, T., Apr. 2012. Transmission grid extensions for the integration of variable renewable energies in europe: Who benefits where? Energy Policy 43, 123–135. http://www.sciencedirect.com/science/article/pii/S0301421511010469

Schafer, A., Heywood, J. B., Jacoby, H. D., Waitz, I. A., 2009. Transportation in a climate-constrained world. MIT Press, Cambridge.

Scher, I., Koomey, J. G., Feb. 2011. Is accurate forecasting of economic systems possible? Climatic Change 104 (3-4), 473–479. http://link.springer.com/article/10.1007/s10584-010-9945-z

Schäfer, A., Jacoby, H. D., Jun. 2006. Vehicle technology under CO2 constraint: a general equilibrium analysis. Energy Policy 34 (9), 975–985. http://www.sciencedirect.com/science/article/pii/S0301421504002873

SCHNEIDER, M., 2009. Fast breeder reactors in france. Science & Global Security 17 (1), 36–53. http://www.tandfonline.com/doi/abs/10.1080/08929880902953013

Schneider, S. H., Dec. 1997. Integrated assessment modeling of global climate change: Transparent rational tool for policy making or opaque screen hiding valueladen assumptions? Environmental Modeling & Assessment 2 (4), 229–249. http://link.springer.com/article/10.1023/A%3A1019090117643

Searchinger, T. D., Hamburg, S. P., Melillo, J., Chameides, W., Havlik, P., Kammen, D. M., Likens, G. E., Lubowski, R. N., Obersteiner, M., Oppenheimer, M., Robertson, G. P., Schlesinger, W. H., Tilman, G. D., Oct. 2009. Fixing a critical climate accounting error. Science 326 (5952), 527–528, PMID: 19900885. http://www.sciencemag.org/content/326/5952/527

Short, W., Blair, N., Sullivan, P., Mai, T., 2009. ReEDS model documentation: base case data and model description. Golden, CO: National Renewable Energy Laboratory.

Sims, R., Mercado, P., Krewitt, W., Bhuyan, G., Flynn, D., Holttinen, H., Jannuzzi, G., Khennas, S., Liu, Y., Nilsson, L. J., Ogden, J., Ogimoto, K., O'Malley, M., Outhred, H., Ulleberg, y., Hulle, F. v., 2011. Integration of renewable energy into present and future energy systems. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Sims, R., Schock, R., Adegbululgbe, A., Fenhann, J., Konstantinaviciute, I., Moomaw, W., Nimir, H., Schlamadinger, B., Torres-Martínez, J., Turner, C., Uchiyama, Y., Vuori, S., Wamukonya, N., Zhang, X., 2007. Ch4: Energy supply. In: Metz, B., Davidson, O., Bosch, P., Dave, R., Meyer, L. (Eds.), Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the IPCC. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Skea, J., Anderson, D., Green, T., Gross, R., Heptonstall, P., Leach, M., 2008. Intermittent renewable generation and the cost of maintaining power system reliability. IET Generation, Transmission & Distribution 2 (1), 82.
http://digital-library.theiet.org/content/journals/10.1049/iet-gtd_20070023

Smil, V., 2000a. Energy in the twentieth century: resources, conversions, costs, uses, and consequences. Annual Review of Energy and the Environment 25 (1), 21–51.
http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.25.1.21

Smil, V., Nov. 2000b. Perils of long-range energy forecasting: Reflections on looking far ahead. Technological Forecasting and Social Change 65 (3), 251–264.
http://www.sciencedirect.com/science/article/pii/S0040162599000979

Stadler, I., Jun. 2008. Power grid balancing of energy systems with high renewable energy penetration by demand response. Utilities Policy 16 (2), 90–98.
http://www.sciencedirect.com/science/article/pii/S0957178707000732

Stanton, E. A., Aug. 2011. Negishi welfare weights in integrated assessment models: the mathematics of global inequality. Climatic Change 107 (3-4), 417–432.
http://link.springer.com/article/10.1007/s10584-010-9967-6

Stanton, E. A., Ackerman, F., Kartha, S., 2009. Inside the integrated assessment models: Four issues in climate economics. Climate and Development 1 (2), 166–184.
http://www.tandfonline.com/doi/abs/10.3763/cdev.2009.0015

Steiner, P. O., Aug. 1957. Peak loads and efficient pricing. The Quarterly Journal of Economics 71 (4), 585–610.
http://qje.oxfordjournals.org/content/71/4/585

Steinke, F., Wolfrum, P., Hoffmann, C., Feb. 2013. Grid vs. storage in a 100% renewable europe. Renewable Energy 50, 826–832.
http://www.sciencedirect.com/science/article/pii/S0960148112004818

Stern, N. N. H., 2007. The economics of climate change: the Stern review. Cambridge University Press.

Stoft, S., 2002. Power system economics: designing markets for electricity. John Wiley & Sons, New York.

Sue Wing, I., 2004. Computable general equilibrium models and their use in economy-wide policy analysis. Technical Note, Joint Program on the Science and Policy of Global Change, MIT.
http://web.mit.edu/globalchange/www/MITJPSPGC_TechNote6.pdf

Sue Wing, I., 2009. Computable general equilibrium models for the analysis of energy and climate policies. In: Evans, J., Hunt, L. C. (Eds.), International Handbook On The Economics Of Energy. Edward Elgar, Cheltenham, pp. 332–366.

Sullivan, P., Krey, V., Riahi, K., Mar. 2013. Impacts of considering electric sector variability and reliability in the MESSAGE model. Energy Strategy Reviews 1 (3), 157–163. http://www.sciencedirect.com/science/article/pii/S2211467X13000023

Toth, F., Mwandosya, M., 2001. Ch10: Decision-making frameworks. In: Metz, B. (Ed.), Climate change 2001: mitigation: contribution of Working Group III to the third assessment report of the IPCC. Vol. 3. Cambridge University Press.

Ueckerdt, F., Hirth, L., Luderer, G., Edenhofer, O., Dec. 2013. System LCOE: what are the costs of variable renewables? Energy 63, 61–75. http://www.sciencedirect.com/science/article/pii/S0360544213009390

UNFCCC Secretariat, 1992. United nations framework convention on climate change. http://www.unfccc.int

UNFCCC Secretariat, 2011. Report of the conference of the parties on its sixteenth session. addendum. part two: Action taken by the conference of the parties at its sixteenth session. Tech. rep., Cancun. http://unfccc.int/resource/docs/2010/cop16/eng/07a02.pdf

van den Bergh, J. C. J. M., Apr. 2004. Optimal climate policy is a utopia: from quantitative to qualitative cost-benefit analysis. Ecological Economics 48 (4), 385–393. http://www.sciencedirect.com/science/article/pii/S0921800904000199

van der Sluijs, J. P., Mar. 2002. A way out of the credibility crisis of models used in integrated environmental assessment. Futures 34 (2), 133–146. http://www.sciencedirect.com/science/article/pii/S0016328701000519

van Vliet, O. P., Faaij, A. P., Turkenburg, W. C., Apr. 2009. Fischer–Tropsch diesel production in a well-to-wheel perspective: A carbon, energy flow and cost analysis. Energy Conversion and Management 50 (4), 855–876. http://www.sciencedirect.com/science/article/pii/S0196890409000041

van Vliet, O. P., Kruithof, T., Turkenburg, W. C., Faaij, A. P., Oct. 2010. Techno-economic comparison of series hybrid, plug-in hybrid, fuel cell and regular cars. Journal of Power Sources 195 (19), 6570–6585. http://www.sciencedirect.com/science/article/pii/S0378775310007688

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., Rose, S. K., Nov. 2011a. The representative concentration pathways: an overview. Climatic Change 109 (1-2), 5–31. http://link.springer.com/article/10.1007/s10584-011-0148-z

van Vuuren, D. P., Stehfest, E., den Elzen, M. G., van Vliet, J., Isaac, M., Sep. 2010. Exploring IMAGE model scenarios that keep greenhouse gas radiative forcing below 3w/m2 in 2100. Energy Economics 32 (5), 1105–1120. http://www.sciencedirect.com/science/article/pii/S014098831000037X

Van Vuuren, D. P., Stehfest, E., Elzen, M. G. J. d., Kram, T., Vliet, J. v., Deetman, S., Isaac, M., Goldewijk, K. K., Hof, A., Beltran, A. M., Oostenrijk, R., Ruijven, B. v., Nov. 2011b. RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C. Climatic Change 109 (1-2), 95–116.
http://link.springer.com/article/10.1007/s10584-011-0152-3

von Hirschhausen, C., Herold, J., Oei, P.-y., Haftendorn, C., 2012. CCTS-Technologie ein Fehlschlag: Umdenken in der Energiewende notwendig. DIW-Wochenbericht 79 (6), 3–9.
http://www.econstor.eu/handle/10419/58090

Waisman, H., Guivarch, C., Grazi, F., Hourcade, J. C., Sep. 2012. The imaclim-r model: infrastructures, technical inertia and the costs of low carbon futures under imperfect foresight. Climatic Change 114 (1), 101–120.
http://link.springer.com/article/10.1007/s10584-011-0387-z

Waisman, H.-D., Guivarch, C., Lecocq, F., 2013. The transportation sector and low-carbon growth pathways: modelling urban, infrastructure, and spatial determinants of mobility. Climate Policy 13 (sup01), 106–129.
http://www.tandfonline.com/doi/abs/10.1080/14693062.2012.735916

Weigt, H., Jeske, T., Leuthold, F., von Hirschhausen, C., Jul. 2010. "Take the long way down": Integration of large-scale north sea wind using HVDC transmission. Energy Policy 38 (7), 3164–3173.
http://www.sciencedirect.com/science/article/pii/S0301421509005503

Weitzman, M. L., Jan. 2009. On modeling and interpreting the economics of catastrophic climate change. Review of Economics and Statistics 91 (1), 1–19.
http://dx.doi.org/10.1162/rest.91.1.1

Weyant, J. P., Aug. 2009. A perspective on integrated assessment. Climatic Change 95 (3-4), 317–323.
http://link.springer.com/article/10.1007/s10584-009-9612-4

Weyant, J. P., Olavson, T., May 1999. Issues in modeling induced technological change in energy, environmental, and climate policy. Environmental Modeling & Assessment 4 (2-3), 67–85.
http://link.springer.com/article/10.1023/A%3A1019012317160

Wiser, R., Yang, Z., Hand, M., Hohmeyer, O., Infield, D., Jensen, P. H., Nikolaev, V., O'Malley, M., Sinden, G., Zervos, A., 2011. Wind energy. In: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

World Bank, Nov. 2012. Turn down the heat : why a 4°C warmer world must be avoided. Tech. Rep. 74455, The World Bank.
http://documents.worldbank.org/curated/en/2012/11/17097815/turn-down-heat-4%C2%B0c-warmer-world-must-avoided

Chapter 2

Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R*

Gunnar Luderer
Robert C. Pietzcker
Elmar Kriegler
Markus Haller
Nico Bauer

*published in *Energy Economics* as Luderer, G., Pietzcker, R.C., Kriegler, E., Haller, M., Bauer, N. (2012) "Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R". Vol. 34, Supplement 3, pp. S378-S390
dx.doi.org/10.1016/j.eneco.2012.07.022

Energy Economics 34 (2012) S378–S390

Contents lists available at SciVerse ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R

Gunnar Luderer *, Robert C. Pietzcker, Elmar Kriegler, Markus Haller, Nico Bauer

Potsdam Institute for Climate Impact Research, Potsdam, Germany

ARTICLE INFO

Article history:
Received 2 June 2011
Received in revised form 18 July 2012
Accepted 26 July 2012
Available online 4 August 2012

JEL classification:
Q40
Q43
Q47
Q54
O53

Keywords:
Climate change mitigation
Mitigation shares
Integrated assessment modeling
Asia
China
India

ABSTRACT

We use the ReMIND-R model to analyze the role of Asia in the context of a global effort to mitigate climate change. We introduce a novel method of secondary energy based mitigation shares, which allows us to quantify the economic mitigation potential of technologies in different regions and final energy carriers.
The 2005 share of Asia in global CO_2 emissions amounts to 38%, and is projected to grow to 53% under business-as-usual until the end of the century. Asia also holds a large fraction of the global mitigation potential. A broad portfolio of technologies is deployed in the climate policy scenarios. We find that biomass in combination with CCS, other renewables, and end-use efficiency each make up a large fraction of the global mitigation potential, followed by nuclear and fossil CCS. We find considerable differences in decarbonization patterns across the final energy types electricity, heat and transport fuels. Regional differences in technology use are a function of differences in resource endowments, and structural differences in energy end use. Under climate policy, a substantial mitigation potential of non-biomass renewables emerges for China and other developing countries of Asia (OAS). Asia also accounts for the dominant share of the global mitigation potential of nuclear energy. In view of the substantial near term investments into new energy infrastructure in China and India, early adoption of climate policy prevents lock-in into carbon intensive infrastructure and thus leads to a much higher long-term mitigation potential.

© 2012 Elsevier B.V. All rights reserved.

1. Introduction

Stabilizing climate change at a level in line with the targets formulated by the international community will require a substantial reduction of greenhouse gas emissions relative to business-as-usual (IPCC, 2007). The recent scenario literature shows that in absence of climate policy further expansion of fossil fuel use would result in an increase of CO_2 emissions from energy and industry by a factor 1.6–5.4 by 2100 relative to year 2000 levels (Fisher et al., 2007; Clarke et al., 2009; Edenhofer et al., 2010; Luderer et al., 2012).

In its 'Copenhagen Accord', the United Nations Framework Convention on Climate Change has adopted the target of limiting the increase in global mean temperature to 2 °C (UNFCCC, 2012). This target implies a tight limit on the remaining budget of anthropogenic greenhouse gas emissions (Meinshausen et al., 2009). The majority of modeling studies that have considered climate change mitigation targets consistent with climate stabilization at 2 °C arrived at 2050 emissions reductions of at least 50% with respect to 2005 levels, and long term emissions that are close to zero or negative at the end of the century (Clarke et al., 2009; Edenhofer et al., 2010). Clearly, emission reductions of this magnitude require a large-scale transformation of global energy systems and a massive expansion of low carbon energy technologies. With their substantial share of global emissions, Asian countries will play an important role in any effort to limit climate change.

Crucial research questions relate to the role of technologies in achieving climate targets (e.g. Nordhaus and Nakicenovic, 2011). What can individual technologies contribute to emission reductions? What are the determining factors for their effectiveness in reducing emissions and how do these factors vary regionally? And which technologies carry the largest part of the mitigation effort? The answer to these important questions is complex, because the role of technologies for mitigating climate change is not determined by their individual characteristics alone. Rather it strongly depends on the entire mitigation pathway characterized by a portfolio of technologies deployed over time.

Integrated Assessment Models (IAMs) with a detailed representation of the energy-economic system cover the relevant dynamics, albeit many in a stylized form, and therefore are well suited for studying the role of technologies in achieving climate targets. This requires deducing their individual contribution to the mitigation effort from the model output. The most common method is to study deployment levels of low-carbon technologies under climate policy and make comparisons to baseline levels (e.g., Calvin et al., 2009; Edenhofer et al., 2010; Krey and Clarke, 2011; Krey and Riahi, 2009; Luderer et al., 2012; van

* Corresponding author.
E-mail address: luderer@pik-potsdam.de (G. Luderer).

0140-9883/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.eneco.2012.07.022

Vuuren et al., 2007). This approach provides an assessment of the technologies supported by climate policy, but does not directly address economic efficiency and mitigation effectiveness. For an assessment of economic efficiency, some studies have considered scenarios in which the expansion of individual low carbon technologies is assumed to be restricted or unavailable (Edenhofer et al., 2010; Krey and Riahi, 2009; Luderer et al., 2012). Comparing mitigation costs in such technology constrained scenarios against scenarios with the full set of technologies available allows the modeler to derive the increase in mitigation costs that arises from the technology restriction. This cost markup provides a good indicator for the contribution of a technology to the economic efficiency in achieving climate targets.

A complementary approach would be to assess mitigation effectiveness, i.e. the contribution of a technology to emission reductions. How can emission reductions be attributed to individual technologies? Although this question seems rather simple, there is no straight-forward way of quantification. The term "Stabilization Wedges" has been coined by Pacala and Socolow (2004), who claimed that the mitigation gap, i.e. the difference between baseline emissions and emission levels required to achieve climate stabilization, can be bridged by a combination of currently available technologies. While such technology wedges have now become a common tool for illustrating climate stabilization pathways to stakeholders and decision-makers (e.g. Edmonds et al., 2000; EPRI, 2007; IEA, 2010; Placet et al., 2004), we are only aware of a few studies in the peer-reviewed IAM literature that use technology wedges (Riahi and Roehrl, 2000; Riahi et al., 2007; Shukla et al., 2008).

A problematic aspect of the Pacala and Socolow approach is the implicit suggestion that mitigation scenarios can be constructed by adding up mitigation wedges, and that individual technology wedges can be used interchangeably. As mentioned above, however, the role of individual technologies cannot be assessed in isolation. Their contribution to emission reduction is an emergent system property. Thus, any method of attributing emission reductions to technologies should be regarded as a diagnostic tool for analyzing mitigation strategies for a given climate policy scenario, rather than a tool for constructing mitigation scenarios. Technology contributions are a function of each other and the mitigation scenario, and cannot be combined arbitrarily. This discussion reflects a fundamental tension between integrated assessment models of climate policy that decidedly take a systems perspective, and bottom-up approaches that try to combine individual mitigation potentials to marginal abatement cost curves (e.g. McKinsey and Company, 2009).

In this paper, we want to take the concept of attributing emission reductions to individual technologies a step further while retaining a strict integrated systems perspective. We introduce a new method for attributing emission reductions as foreseen in mitigation scenarios from IAMs to individual technologies. This is a purely diagnostic tool for decomposing the mitigation effort. Due to the system dependency, the resulting mitigation shares per technology cannot be taken out of context and recombined to different mitigation scenarios. In order to avoid confusion with the popularized concept of mitigation wedges that has been used frequently in the latter way, we will call the fraction of emission reductions attributed to a specific technology a "mitigation share" in the following.

The value of mitigation shares lies in synthesizing model output on the regional and sectoral (different secondary energy types) level into a coherent perspective of the low-carbon transformation. In terms of mitigation effectiveness, the emission intensity of the replaced technology mix matters, which differs across regions (e.g. coal-intensive energy systems vs. energy systems with a substantial share of nuclear) and final energy types (e.g. electricity vs. transport fuels). Secondary energy based mitigation shares capture these heterogeneities in aggregating mitigation contributions of technologies. While the methodology is a useful tool as a diagnostic tool for comparing different scenarios from a single model, it is important to note that its usefulness for comparing results across models is constrained by its strong dependence on model-specific properties, such as the resolution of technologies and energy carriers. Its application across models would require a standardized output on energy conversion routes which has not yet been established.

The regional focus of the paper is on Asia and a comparison with other key emitting regions such as the USA and the European Union. A number of studies have analyzed mitigation potentials and emission reduction strategies in Asia (Jiang et al., 2000; Kainuma et al., 2003) or individual countries of Asia, in particular China (e.g., Chen, 2005; Chen et al., 2007; Jiang and Hu, 2006; Steckel et al., 2011) and India (Shukla et al., 2008). The focus of our study is to analyze climate change mitigation in the context of the global effort. We apply the newly proposed decomposition method to the AME scenarios from the integrated assessment model ReMIND to investigate the following research questions: What are the most significant mitigation technologies, and how does their emission reduction potential compare across different final energy types? How do realized mitigation potentials of technologies change with increasing stringency of climate policy? How do mitigation potentials and decarbonization strategies compare across regions within Asia and between Asia and the rest of the world?

We finally apply the model and analysis framework to explore if there is a benefit of early adoption of climate policies in Asia. Previous studies found that fragmented climate policy regime result makes mitigation targets more difficult to achieve (Clarke et al., 2009; Jakob et al., 2012). Bosetti et al. (2009) and Richels et al. (2009) showed that the anticipation of future binding climate targets in developing countries influences near-term investment decisions, thus avoiding high-carbon lock-ins. We approach the matter by contrasting scenarios with immediate adoption of climate policy by all world regions with a scenario in which Asian countries are assumed to delay climate policies until 2020.

Our paper is structured as follows: In the next section, the model and scenario setup are introduced. Section 3 describes the methodological approach for the calculation of secondary energy based mitigation shares, and how it is distinguished from other approaches of determining the contribution of technologies to mitigation. Section 6 presents results from global and cross-sectoral perspective. Region specific results for Asia are reported in Section 7, along with an analysis of the role of early climate policy action in Asia. A broader discussion of caveats to the use and interpretation of the methodology are discussed in Section 6, followed by a concluding summary of the paper.

2. Model and scenario setup

The Refined Model of Investment and Technological Development ReMIND in its version 1.3 is used for this study. It is a global Integrated Assessment Model that represents 11 world regions and considers the time horizon from 2005 to 2100. A detailed description of this model is available from previous publications (Leimbach et al., 2010), and the technical model documentation (Luderer et al., 2010).

ReMIND is composed of three components: (a) the macro-economic growth module that describes socio-economic developments and determines the economy's demand for final energy, (b) a detailed energy system module describing the conversion pathways from various types of primary energy via secondary energy to final energy, and (c) a climate module that simulates the response of the climate system to anthropogenic emissions of greenhouse gasses and other forcing agents. A key feature of the model is that all three components are solved in an integrated, intertemporal optimization framework, thus fully accounting for feedbacks between all components of the system (Bauer et al., 2008).

In particular in terms of its macro-economic formulation, REMIND-R resembles well-known energy-economy-climate models like RICE (Nordhaus and Yang, 1996) and MERGE (Manne et al., 1995). REMIND-R is characterized by a comparatively high technological resolution on the supply side of the energy system (70 conversion technologies with detailed vintage structures), the consideration of technological learning in the energy sector, and the representation

of trade relations between regions. This results in a high degree of where-flexibility (abatement can be performed where it is cheapest), when-flexibility (optimal timing of emission reductions and investments), and what-flexibility (optimal allocation of abatement among emission sources) for the mitigation effort.

The scenarios used for this study (Table 1) are based on the harmonized scenario set used for the AME intercomparison exercise comprising of one reference scenario, three scenarios with a prescribed global carbon tax, and two climate stabilization scenarios (Calvin et al., this issue). For the tax scenarios, the revenues are redistributed to the representative households, and thus are available for consumption or savings.

Many Asian countries have already adopted climate mitigation measures. In order to test the value of early adoption of climate policy, we prepared a variant of the TAX-30 scenario as an addition to the standard AME scenarios. In this (counter-factual) delay2020 scenario, the Asian macro-regions China, India, and other Asian developing countries are assumed to follow their business-as-usual trajectory without emissions pricing until 2020 and without anticipation of future climate policy, while all other world regions implement a uniform carbon tax already in 2015. The Asian regions are assumed to adopt the globally uniform tax from 2025 onwards.

3. Secondary energy based mitigation shares

3.1. Description of methodology

This section describes the methodology of secondary energy based mitigation shares used in this paper. A full documentation of the methodology is provided in supplementary material. The basic rationale is to consider climate-policy-induced changes in the technology portfolio for each region, time period, and secondary energy type, and to attribute emission reductions to individual energy conversion technologies. The method is unique in the sense that it tracks substitutions within the energy sector at the finest resolution represented in the model. It is composed of six distinct steps (the indices for region r and time t have been omitted for better readability):

1. For each technology i and secondary energy type j, calculate the difference of production between baseline and policy scenario ΔS_{ij}:

$$\Delta S_{ij} = S_{ij}^{pol} - S_{ij}^{bau}$$

2. Calculate emission intensities ε_{ij} for each technology i producing secondary energy carrier j:

$$\varepsilon_{ij} = \frac{E_{ij}}{S_{ij}}$$

where E_{ij} are the emissions caused by the technology. In the case of joint production, emissions for each technology are distributed across products according to the relative shares of energy output.

3. Calculate the average emission intensity $\overline{\varepsilon}_j$ of replaced production of secondary energy carrier j:

$$\overline{\varepsilon}_j = \frac{\sum_{i:\Delta S_{ij}\le 0}\left(E_{ij}^{pol} - E_{ij}^{bau}\right)}{\sum_{i:\Delta S_{ij}\le 0}\Delta S_{ij}}$$

where the sums run over all technologies with deployment ΔS_{ij} lower than in the baseline.

4. For all conversion technologies i that are deployed at higher levels than in the baseline, calculate mitigation contribution M_{ij} for the production of secondary energy carrier j:

$$M_{ij} = \begin{Bmatrix} \Delta S_{ij}\left(\overline{\varepsilon}_j - \varepsilon_{ij}\right) & if \quad \Delta S_{ij} > 0 \\ 0 & if \quad \Delta S_{ij} \le 0 \end{Bmatrix}.$$

The mitigation contribution is assumed to be zero for technologies with deployment lower than in the baseline. Note that M_{ij} will be positive for all technologies with emission intensities ε_{ij} smaller than the average emission intensity of the replaced technologies. This is usually the case, since climate policy will result in expansion of low emission technologies. The technology-specific emission intensities can differ between baseline and policy cases, e.g. because of different vintage structures. As explained in detail in the supplementary material, an additional term arises in this equation, if ε_{ij} in the policy case is different from the baseline value. Since this contribution is very small, and for the sake of conceptual clarity, we omit it here.

5. For each secondary energy carrier j, calculate the contribution of adjustments in energy end-use to emission reductions. These terms capture both the reductions in final energy demand and substitutions between final energy carriers.

$$M_j^{end} = -\sum_i \left(S_{ij}^{pol} - S_{ij}^{bau}\right)\overline{\varepsilon}_j$$

Note that M_j^{end} can become negative if the secondary energy demand j is higher in the policy case than in the baseline. For some of the scenarios considered, we find electrification of energy end use to result in higher electricity consumption than in the baseline, thus yielding a negative end-use share for electricity. In line with intuition, however, this is found to be smaller than the end-use related emission reduction from non-electric end use. As discussed in Section 3.2, the treatment of such substitutions on the end-use level is a key source of ambiguity in the methodology.We can proof that the sum of all technology contributions M_{ij} and the end-use contribution M_j ^{end} is equal to the difference of baseline and policy emissions (see supplementary online material). Hence, the decomposition of emission reductions into the above components is complete. An important feature of this approach is thus that the end-use contribution is calculated explicitly, rather than determined as the residual of the mitigation gap.

Table 1
Description of reference and climate policy scenarios used. REF, TAX scenarios, as well as 3.7NTE and2.6OS are part of the harmonized scenario set of the AME study. delay2020 is a complementary scenario conducted for this paper.

AME scenario name	Description	Short descriptor
Reference	Reference scenario. No climate policies beyond Kyoto Reductions for EU and Japan.	REF
CO_2 price \$10 (5% p.a.)	CO_2 pricing scenarios with globally uniform tax starting from 2015 increasing at a rate of 5% p.a. 2020	TAX-10
CO_2 price \$30 (5% p.a.)	price levels are \$10, \$30, \$50, respectively.	TAX-30
CO_2 price \$50 (5% p.a.)		TAX-50
3.7 W/m^2 NTE	Stabilization scenarios aiming at radiative forcing at 3.7 W m^{-2} (550 ppm CO_{2e}, not-to-exceed), and	3.7NTE
2.6 W/m^2 OS	2.6 W m^{-2} by 2100 (450 ppm CO_{2e}, overshooting allowed).	2.6OS
	Variant of TAX-30 scenario with Asian developing countries myopically following reference scenario until 2020. Asia adopts carbon tax in 2025, all other world regions in 2015.	Delay2020

6. For 11 regions, 48 primary to secondary energy conversion technologies and 9 secondary energy carriers represented in ReMIND-R, steps 2 and 3 result in some 450 non-zero summands of individual reduction contributions for each time step. For the further analysis, we thus group these 'micro-shares' into different technology categories, final energy types, and region groups.

3.2. Relation to alternative approaches

A number of alternative approaches for calculating the economic mitigation potential of technologies have been used in the literature or are conceivable. The choice of methodology can have a strong influence on the resulting relative size of mitigation shares.

In view of differences in methodologies which potentially have a strong effect on the results, it is important to consider the advantages and disadvantages of the alternative approaches. In order to structure the discussion, it is helpful to distinguish between three types of energy system adjustments in response to climate policy: (a) substitution between secondary energy supply technologies (e.g. substituting nuclear for coal in electricity production), (b) substitution between different final energy carriers (e.g. using electricity instead of liquid fuels in transport), and (c) final energy demand reduction (e.g. more efficient appliances or insulation of buildings, or reduction of energy service demand). We thus propose to evaluate alternative methodologies based on their ability to capture the energy system transformation in terms of the substitutions and adjustments occurring in the model.

By choice of an accounting method, implicit assumptions about substitutions between baseline and climate policy case are made. Methods can thus be categorized according to their assumptions about substitutions. In many studies, the mitigation contribution is calculated based on changes in primary energy consumption, e.g. in Edmonds et al. (2000), and Riahi and Roehrl (2000). Such a calculation based on primary energy is problematic for several reasons. First, there is no unambiguous way of primary energy accounting (Lightfoot, 2007; Macknick, 2011; IPCC, 2011, Annex II). This ambiguity in primary energy accounting translates directly to ambiguity in the calculation of CO_2 emission mitigation contributions (cf. Supplementary Online Material). Secondly, climate policy will induce substitutions on the level of secondary energy production (e.g. by replacing electricity from coal with electricity from nuclear power), or on the level of final energy demand (e.g. by a switch from non-electric final energy demand in households and industry to electricity). Such substitutions will not necessarily result in a one-to-one substitution on the primary energy level. Thirdly, related to the second point, different secondary energy carriers have different conversion efficiencies and emission intensities. For accurate accounting how much each energy carrier contributes to reduce emissions matters, for instance, if renewable energy replaces fossils in electricity production (where one unit of wind or solar primary energy replaces some two to three units of fossil primary energy), or to produce heat (where renewables and fossils have similar conversion efficiencies). This difference is not captured by primary energy accounting.

Secondary energy based economic mitigation potentials as calculated with our approach alleviate some of the problems associated with the primary energy based calculation. Much of the ambiguity associated with primary energy accounting is eliminated, because substitutions are tracked in terms of secondary energy production in physical quantities. The approach also fully differentiates according to emission intensities of different secondary energy types. The contributions of final energy demand reductions are accounted for in terms of avoided emissions that would have occurred if the energy had been produced with the technology mix deployed in the baseline scenario. In principle, it would also be possible to calculate the efficiency contribution based on the carbon intensity in the policy scenario. However, this would result in abatement credits (i.e., emission reduction per unit of secondary energy produced) for zero-carbon technologies that exceed baseline emission levels, and thus would be implausibly high.

A key limitation and source of ambiguity in the approach is, however, the treatment of substitutions between final energy carriers, for instance increased the use of electricity in lieu of gas or coal for industry which are treated in terms of secondary energy demand changes. If one energy carrier is expanded to substitute for another, a negative end-use mitigation share for the expanded FE carrier is calculated, and a positive end-use mitigation share for the FE carrier that contracts. The composite end-use contribution is then calculated as the sum of both end-use shares. It is important to note that this approach deviates from the paradigm of tracking substitutions according to the model mechanics. In the supplementary material section, the effect of using alternative approaches for treating negative end-use shares is explored and found to have a noticeable but moderate effect on the results. The treatment of changes in end-use crucially depends on the model representation of the demand side, thus limiting the comparability of mitigation shares calculated for different models.

For a model with detailed representation of end-use, it would in principle be possible to calculate end-use based mitigation shares. This would involve the following steps: (i) identification of all possible energy service supply pathways from primary energy to secondary energy to energy service (e.g. conventional cars with petrol, conventional cars with biofuels, electric cars with renewables, electric cars with nuclear etc. for the provision of passenger transport), and their deployment differences between baseline and policy case, (ii) calculation of the emission intensity of energy service supply of all alternative supply pathways (e.g. in gCO_2 per passenger kilometer), (iii) calculation of the baseline emission intensity for each energy service, (iv) calculation of the mitigation share of each energy supply pathway (micro-shares), and (v) aggregation of these micro-shares into reasonable technology groups to obtain aggregate mitigation shares. These steps would be analogous to our methodology of secondary based mitigation shares presented in Section 3.2. It is important to note, however, that the practicability of tracking a huge number of possible conversion pathways in a highly complex energy system is a crucial limitation of such an approach. Moreover, ad-hoc assumption would be required to split between the supply side contribution (e.g. renewable electricity instead of petroleum) and end use technology contribution (electric instead of conventional cars), which will always be to some extent ambiguous. This challenge is akin to the split between carbon intensity and energy intensity improvements in Kaya-type decomposition analysis (e.g. Ang, 2004). Since ReMIND does not have a detailed representation of energy services, such an extension is clearly beyond the scope of our paper, but it would be a worthwhile topic for subsequent research.

4. Economic mitigation potential of technologies

4.1. The global perspective

In order to achieve climate stabilization, emissions have to be reduced substantially compared to business-as-usual. The scale of this challenge is illustrated in Fig. 1. Under our baseline scenario, which describes a world without any climate policy, emissions from the energy system would more than double between 2005 and 2060, and slightly decrease thereafter. Driven by a nine-fold increase in gross world product between 2005 and 2100, the scale of the global energy system would reach almost 1200 EJ/yr in terms of primary energy use[1] (Fig. 2). This increase is largely driven by an increase in coal use. Our medium tax scenario TAX-30 results in a climate forcing of 2.9 W m^{-2} by 2100, roughly consistent with the 2 °C target. Global energy-related CO_2 emissions peak in 2020 and decline to negative net emissions by 2080.

[1] Primary energy demand is expressed in direct equivalent terms, see IPCC (2011, Annex II) for a detailed discussion of primary energy accounting methods.

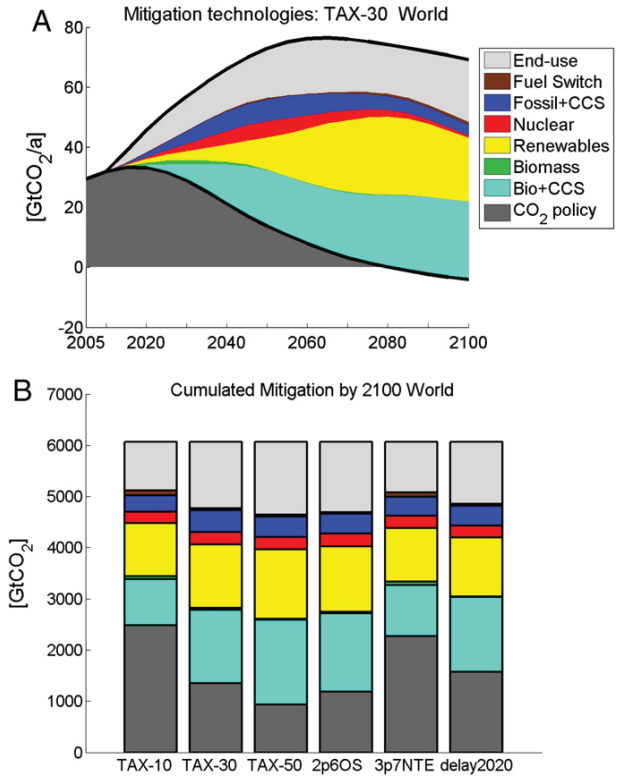


Fig. 1. (A) Emission gap between the baseline scenario and the TAX-30 climate policy scenario. The emission reductions induced by climate policy are decomposed into six technology groups as well as the contribution of changes in end-use. (B) Global emission reductions cumulated 2005–2100 for different climate policy scenarios.

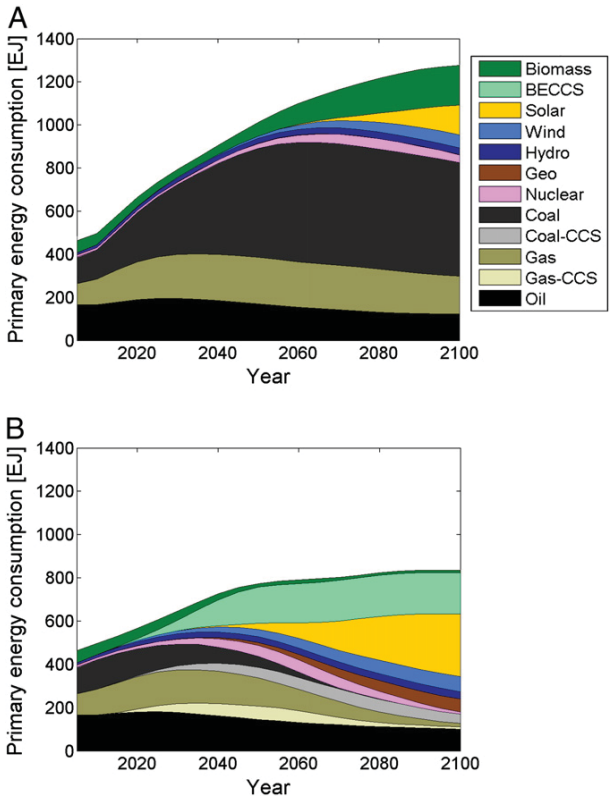


Fig. 2. Primary energy consumption (direct equivalent accounting) in (A) the baseline, and (B) the TAX-30 climate policy scenario.

Based on the methodology outlined in Section 3, the emission reductions performed relative to the baseline scenario can be attributed to the technology groups fossil fuel switch, fossil CCS, biomass without CCS, biomass with CCS, other renewables, nuclear, as well as improvements in end-use efficiency. This analysis reveals that the bulk of the mitigation effort is borne by bioenergy use with CCS (BECCS), non-biomass renewables, and end-use efficiency. It is important to note that the end-use share accounts not only for the improvements of demand side efficiency in using various final energy carriers, but also for the substitution from energy carriers that are less efficient or more carbon intensive to those that are more efficient and less carbon intensive, e.g. increased use of electricity instead of solids in households and industry. The share of end-use efficiency in total abatement is particularly high initially, and continues to contribute substantially to the mitigation effort throughout the century. The significance of biomass lies (a) in its versatility as primary energy carrier for transport fuels, electricity production, and non-electric secondary, and (b) in the possibility to generate negative net emissions using BECCS. For this study we assumed a resource constraint on the availability of bioenergy that increases from 2005 deployment levels of 55 EJ to 200 EJ in 2050. With this constraint, the main contribution of biomass to emissions abatement comes from redirecting bioenergy feedstocks to BECCS conversion pathways, rather than the expansion of bioenergy production. ReMIND considers a variety of BECCS conversion technologies, ranging from biomass based internal gasification combined cycle power plants (Bio-IGCC), to biomass-to-liquid, bio-gasification, and biomass-based hydrogen production. Non-biomass renewable deployment is dominated by wind energy, solar photovoltaic, and concentrating solar power, all of which contribute substantially to the provision of carbon-free electricity in the climate policy scenario.

The expansion of nuclear energy and the introduction of fossil CCS contribute at a smaller scale, and their contribution declines in the 2nd half of the century. We assume a constraint on global uranium availability of 23 MtU_3O_8,[2] which limits the long-term deployment level of nuclear. Fuel recycling of uranium and the use of alternative nuclear fuels are assumed to be unavailable. The competiveness of fossil vis-à-vis carbon-free alternative technologies decreases with increasing carbon prices due to the significant residual emissions, thus making fossil CCS less attractive in the long term. Fuel switch (i.e. use of less carbon-intensive fossil fuels, e.g. natural gas in lieu of coal) only have negligible contributions to the mitigation effort. At the level of ambition considered here, fuel switch is unattractive due to the small emission reductions compared to advanced low carbon technologies.

The dominance of BECCS, other renewables, and end-use efficiency in global emission reductions is robust over the entire set of climate policy scenarios (Fig. 1b). Their realized emission reduction potential increases with increasing climate policy ambition and carbon prices. The contribution of nuclear remains almost constant, largely due to the limited uranium resource. Similarly, the cumulated economic mitigation potential for fossils with CCS is similar across scenarios, because in the high carbon price scenarios higher and earlier deployment of CCS in the first half of the century is offset by lower deployment of CCS in the later decades. Fuel switch from coal to gas accounts for a small portion of emission reductions in the TAX-10 and 3.7NTE scenarios, but becomes increasingly insignificant for the more ambitious scenarios.

Table 2 provides an overview of the scenarios considered. The reference scenario results in a cumulated emissions budget from fossil fuel use of 6.0 $TtCO_2$ for the time horizon 2005–2100. An increase of

[2] This constraint is based on the values given in the 2009 "Red Book" (NEA, 2009). It excludes the extraction of uranium from sea water and assumes recovery factors of ~0.5 for undiscovered and unconventional resources.

Table 2
Overview of scenario results in terms of cumulative CO_2 emissions from fossil fuels and industry; cumulative emissions of CO_2, N_2O and CH_4; anthropogenic radiative forcing (including long-lived GHGs, aerosols, and other forcing components); increase of global mean temperature relative to pre-industrial levels; and mitigation costs in terms of cumulated consumption losses relative to baseline discounted at 5%. A climate sensitivity of 3 °C was used in the climate model for the estimation of GMT increase. The probability of exceeding 2 °C is based on 2000–2050 cumulative CO_2 emissions and calculated using lookup table provided by Meinshausen et al. (2009).

Scenario	CO_2 FF&I 2005–2100 [10^3 $GtCO_2$]	GHG 2005–2100 [10^3 $GtCO_2$]	Forcing in 2100 [W m^{-2}]	2100 GMT increase [°C]	Prob. of exceeding 2 °C	Mitigation costs
REF	6.1	8.1	6.0	3.5 °C	100%	–
TAX-10	2.5	3.8	3.7	2.5 °C	88%	0.4%
TAX-30	1.4	2.5	2.8	2.0 °C	52%	1.1%
TAX-50	0.94	2.0	2.5	1.8 °C	37%	1.7%
3.7NTE	2.3	3.5	3.7	2.4 °C	78%	0.6%
2.6OS	1.2	2.1	2.6	1.9 °C	39%	1.4%
delay2020	1.6	2.7	3.0	2.1 °C	66%	1.0%

radiative forcing to 6.0 W m^{-2} would result, with a transient temperature response of 3.5 °C by 2100, assuming a climate sensitivity of 3 °C. The carbon tax scenarios result in reductions of cumulated CO_2 emissions to 2.5 $TtCO_2$ (TAX-10), 1.4 $TtCO_2$ (TAX-30), and 0.94 $TtCO_2$ (TAX-50). Emission budgets for the climate stabilization scenarios 3.7NTE and 2.6OS are 2.3 and 1.2 $TtCO_2$, respectively. The tax scenarios lead to radiative forcing levels of 2.5–3.7 W m^{-2}. While three of the policy scenarios have a medium (TAX-30) or above 50% likelihood (TAX-50, 2.6OS) of reaching the 2 °C target, the TAX-10 and 3.7NTE scenarios would likely fall short of this target.

The ordering of mitigation costs corresponds to that of emission budgets. The cumulated discounted consumption losses incurred by climate policy range from 0.4% (TAX-10), 0.6% (3.7NTE), to 1.1% (TAX-30), 1.5% (2.6OS), and 1.6% (TAX-50). A strongly convex cost pattern emerges: incremental mitigation costs increase substantially with increasing levels of climate policy ambition.

4.2. Decarbonization of end-use

The method of secondary energy based mitigation shares makes it possible to attribute the mitigation effort to the three final energy types electricity, heat, and transport fuels. In ReMIND-R, electricity is exclusively used for in the stationary sector, i.e. for residential, commercial and industry. The "heat" group of final energy carriers comprises all non-electric energy carriers for the stationary sector that are represented in the model: solids, liquids, gasses, centralized and distributed heating, as well as hydrogen. Transport fuels considered are petrol, diesel, and hydrogen. Electrification of transport (e.g. electric vehicles) is not represented in ReMIND-R. In 2005, electricity generation worldwide accounted for emissions of 9.8 $GtCO_2$, while emissions from heat production (households and industry) and transport were 12.5 $GtCO_2$, and 7.2 $GtCO_2$, respectively.[3]

Fig. 3(a) breaks down emission reductions for the TAX-30 scenario by the final energy types electricity, heat and transport. The analysis reveals that mitigation contributions and decarbonization patterns differ considerably across these three different final energy types. An array of supply-side low-carbon alternatives is available for the power sector: renewables (mostly wind, photovoltaics and concentrating solar power), nuclear power, and CCS with fossils or biomass. As a consequence, cumulative emissions are reduced to 7% of the emissions that would occur under business-as-usual. In ReMIND-R, much fewer technology options are both available and economic for non-electric energy, therefore heat and transport fuels account for the bulk of the residual CO_2 emissions from the energy system. In the transport sector, the production of synfuels and H_2 from biomass, and to a lesser extent also from coal, in combination with CCS are the most important mitigation technologies in our model. End-use (efficiency improvements and demand reduction) accounts for about a third of emission reductions relative to the reference scenario.

Heating is characterized by the highest share of residual emissions (35% of reference levels). The relevant supply-side mitigation technology options used by the model are methane and hydrogen production from BECCS, and non-biomass renewables for low-temperature heat. They combine to a reduction of 26% relative to reference levels. The dominant share of emission reductions (37%) in the heat sector originates from end-use: In addition to the reduction of energy intensity, the shift to electricity as a final energy carrier contributes strongly. Conversely, based on the emissions accounting methodology used here, the resulting increase of electricity demand yields a negative contribution of end-use for electricity.

The difficulty of decarbonizing heat and transport hints at a dominant role of these end-use types in defining the lower limit of achievable reduction targets ("feasibility frontier", cf. Knopf et al., 2011). Fig. 3(b) provides a complementary perspective on sectoral emission patterns by decomposing residual fossil emissions and the negative BECCS contribution by end-use types. The fossil fuel emissions from the power sector are dominated by residual emissions from existing vintages of present

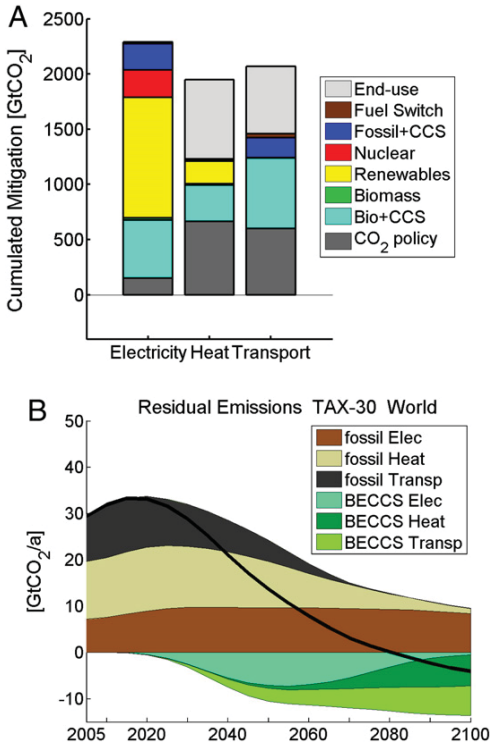


Fig. 3. (A) Mitigation contribution of technologies cumulated from 2005 to 2100, and broken down by the final energy types electricity, heat, and transport fuels for the TAX-30 climate policy scenario. (B) Residual emissions decomposed by end-use sector. The solid black line in (B) indicates net emissions.

[3] ReMIND 2005 data are calibrated to IEA Energy Balances IEA, 2007a, IEA, 2007b)

generation capacities. These emissions decline gradually as old vintages of fossil-based power generation capacities are replaced by low-carbon alternatives. Fossil emissions from heat production remain substantial, and decrease only gradually in the 2nd half of the century, when an increasing share of the global bioenergy becomes available for this sector. Due to the lack of competitive alternatives, fossil fuel emissions from the transport sector remain above 2005 levels throughout the century, despite the considerable increase of carbon prices.

5. Climate change mitigation in Asia

5.1. Emissions abatement and technologies

Asia[4] accounted for 36% of global energy-related CO_2 emissions in 2005. In absence of climate policy, emissions are projected to increase more than three-fold over the course of the century, resulting in a 53% share of global emissions in 2100. The introduction of a price on carbon is found to result in a substantial decrease of CO_2 emissions (Table 3).

Emission trends in the reference scenario differ considerably across world regions, largely driven by differences in socio-economic developments, energy resource potentials, and patterns of energy end-use. Similarly, domestic abatement efforts and the role of technologies in realizing emission reductions vary according to regional specificities.

Fig. 4 illustrates regional primary energy consumption in selected regions. Until mid-century, the bulk of the energy supply is provided by fossil fuels. China, India, Japan and USA are projected to rely heavily on coal, thus their energy systems are highly emission-intensive. By 2100, an increasing share of energy supply comes from wind, solar and biomass, particularly in the USA, China, OAS and other developing countries. When comparing 2100 China to India, the larger share of nuclear primary energy in India can be traced back to the model assumptions about higher import and transportation costs for coal in India compared to China, while the transportation costs for uranium are negligible. Under climate policy, fossil use is scaled back substantially in all world regions.

For the TAX-30 scenario, biomass and nuclear is expanded considerably compared to REF in 2050, and fossil-CCS is deployed at large scale. It is noteworthy that about four fifth of the global nuclear energy is projected to be deployed in Asia. By the end of the century, primary energy supply is dominated by renewables. Strong regional differences emerge in particular in terms of the role of solar energy, which has the highest resource potential in China, OAS, USA and other developing countries. Biomass use plays an important role in Russia (included in othIC), as well as Latin America and Africa (included in othDC).

As shown in Section 4.2, the sectoral structure of energy end-use affects technology options for climate change mitigation. Current patterns of final energy exhibit strong regional patterns (Fig. 5): In 2005, the role of transport fuels in final energy use in the Asian regions is less significant compared to the USA and Europe. The share of electricity in end-use is comparatively small for developing countries. Based on our assumptions on at least partially converging final energy use patterns, we project increasing electrification and an increase in the demand for transport fuels in the developing world. The effect of climate policy on final energy is two-fold: First, it results in a substantial contraction of final energy demand in all world regions, and second it tends to increase the share of electricity in final energy use. This shift to electricity can be attributed to the large relative price increase of transport fuels and heat sources due to climate policies: Going from BAU to TAX-30, prices for natural gas and oil products at the end-user level increase by 100–400% in the second half of the century due to the carbon taxes, while average electricity prices only increase by 10–50%. These price differences are caused by the large number of decarbonization options for power supply, while the options for transport fuels or heat that are modeled in ReMIND are much scarcer (see Fig. 3).

Table 3
Overview of regional cumulative energy-related CO_2 emissions for the different scenarios.

Scenario	CO_2 fossil fuel and industry emissions 2005–2100 [$GtCO_2$]				Asian share of global total
	CHN	IND	OAS	JPN	
REF	1.47×10^3	469	702	160	46%
TAX-10	603	249	258	76	48%
TAX-30	357	122	182	62	53%
TAX-50	262	85	141	58	58%
3.7NTE	568	225	254	74	49%
2.6OS	316	110	169	60	55%
delay2020	514	180	210	61	61%

Fig. 6 illustrates regional decarbonization patterns for the time span from 2005 to 2100, both in relative and in absolute terms. The reductions in cumulative emissions relative to BAU levels in the climate policy scenarios provide an indication of the economic mitigation potential. Under the TAX-30 climate policy scenario, global cumulative emissions contract to one fifth of the emissions that would occur under BAU. Regional abatement potentials vary strongly, with Europe and Japan reducing no more than 55% and 60% of BAU emissions, while other world regions (in particular biomass-rich Russia, Latin America and Africa) are almost carbon neutral over the course of the century. Renewable potentials, both biomass and non-biomass renewables, are found to be key drivers of regional decarbonization patterns. According to the renewable resource estimates used for ReMIND (Trieb et al., 2009) China features a high-quality solar resource potential, thus these technologies contribute strongly to emissions abatement. In India, by contrast, the resource potential of non-biomass renewables is currently estimated to be of lesser quality, making BECCS and end-use efficiency somewhat more important.

5.2. The significance of early action: Asian developing countries

The rapidly developing economies of Asia have recorded considerable increases of greenhouse gas emissions over the past years (e.g. Raupach et al., 2007). Our baseline projects a further rapid increase of emissions if no climate policy is implemented, due to continued economic growth, and a strong reliance on coal as a source of energy. In order to satisfy the growing energy demand, substantial investments into energy infrastructure are required. This is exemplified by the rapid expansion power sector as shown in Fig. 7. In absence of climate policy, the bulk of the near term investments in China and India will go to coal-based installations. OAS is less coal-reliant in the near term, as it has cheaper gas reserves than India or China. In the medium term, the share of nuclear in investments increases substantially. Even without climate policy, investments in renewables are significant, and account for a dominant share of power sector investments by the end of the century. It is important to note, however, that the share of investments into renewables and nuclear tends to overstate their share in electricity production, since capital expenditure is much higher for these technologies than for fossil-based installations.

Climate policy has several effects on power sector investments. In both China and India, investments into conventional coal-fired power plants decline rapidly and vanish after 2020, as the carbon taxes quickly make electricity from coal uneconomic. In the medium to long-term, as the capital-intensive nuclear and non-biomass renewable technologies account for an increasing share of new installations, the overall scale of investments increases substantially. After 2070, renewable investments decrease due to a stabilization of electricity demand and limitations in the renewable resource potential. As coal is phased out and nuclear electricity is initially cheaper than that from renewable technologies, nuclear investments are brought forward in the climate policy case compared to the baseline. In the case of India, nuclear investments

[4] In this study, we consider the four Asian regions China, India, Japan, and OAS (other developing countries of Southern, Eastern, and Southeastern Asia as well as Korea). We refer to the aggregate of these four regions as “Asia”.

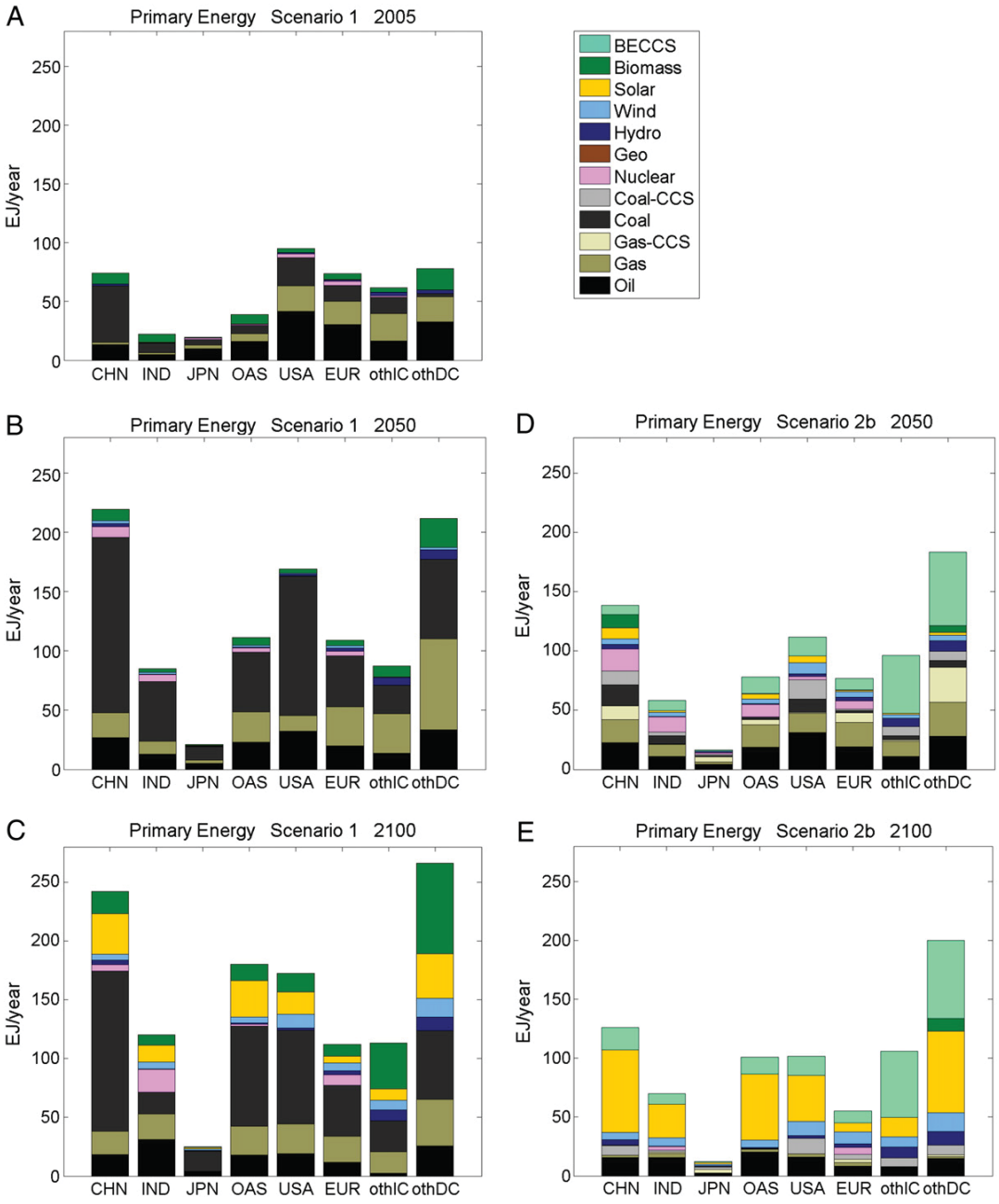


Fig. 4. Regional PE mixes (direct equivalent accounting for nuclear and non-biomass renewables) for different world regions in 2005, 2050 and 2100. Left column: REF scenario; right column: TAX-30 scenario (othIC: other industrialized countries; othDC: other developing countries).

in the 2nd half of the century are smaller than in the reference case, due to a depletion of global uranium resources, and the increasing competiveness of wind and solar energy.

In view of the large investment needs in developing Asia, as well as the strong effect of climate policy on near-term investments the question arises to what extent near-term climate policy affects energy system emissions in the long-term. In order to contrast the short-term and long-term effects of early adoption of climate policy, we constructed a variant of the TAX-30 scenario ("delay2020") in which China, India, and other developing countries of Asia were assumed to delay climate policy and to follow the reference development myopically until 2020, while other world regions adopt the uniform carbon tax from 2015. The Asian regions are assumed to join the global climate mitigation effort in 2025 by adopting the carbon tax. Considering the substantial climate mitigation efforts that are already under way in Asia, it is important to note the assumption of no climate policy until 2020 presents an already counter-factual development. For instance, China's Copenhagen Pledges in terms of reductions of the emission intensity of GDP and the low-carbon share in primary energy provision are roughly in line with our TAX-30 scenarios. By contrasting our hypothetical delay2020 scenario with immediate adoption of climate policy in all world regions, we cannot only analyze how near-term emissions decrease in response to climate policy, but also how early action influences the achievability of deep emission cuts in the medium to long-term future.

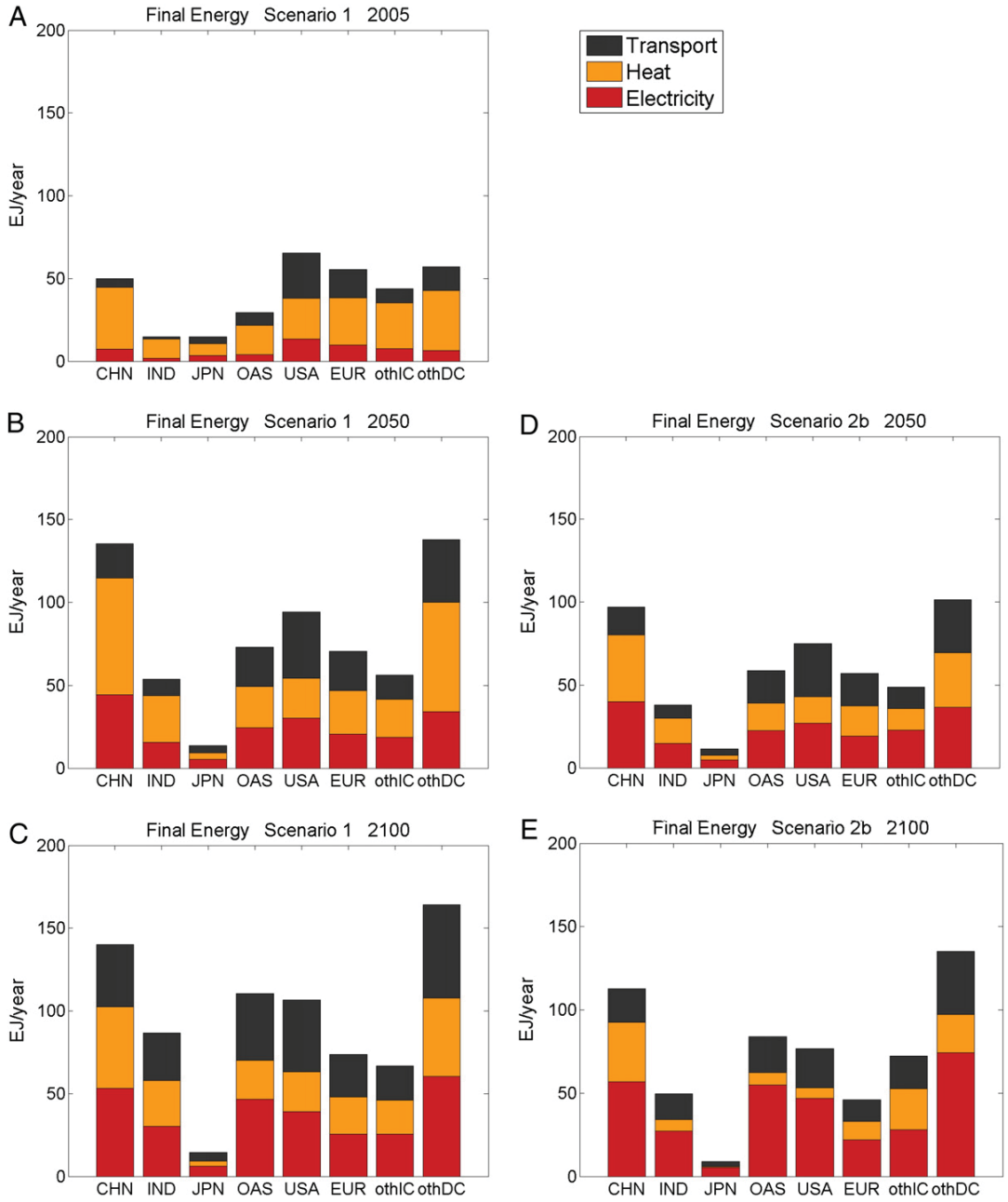


Fig. 5. Regional final energy consumption by end-use type electricity, heat and transport for different world regions in 2005, 2050 and 2100. Left column: REF scenario; right column: TAX-30 scenario (othIC: other industrialized countries; othDC: other developing countries).

Fig. 8 shows mitigation shares for both the TAX-30 and the delay2020 case for China, India, and OAS. Immediate adoption of climate policy results in a peaking of energy-related emissions in 2020 at a level of 7.2 $GtCO_2$ (China), or 2025 at a level of 1.9 $GtCO_2$ (India) and 3.0 $GtCO_2$ (OAS). For a delay in climate policy, the time of peaking remains unchanged for China and India, but emission levels in 2020 are 56% higher than in the case of China, 69% higher in the case of India, and 26% in the case of OAS.

Due to the lock-in into carbon-intensive energy generation capacities, the effect of delay on long-term emissions is substantial.[5] For delay2020, emission levels in 2050 are still 1.9 $GtCO_2$ (China) and 1.1 $GtCO_2$ (India) higher, respectively, than in the TAX-30 scenario with immediate action. The emissions of China cumulated from 2005 to 2100 in the delay2020 case are 513 $GtCO_2$, roughly 44% higher than in TAX-30. In the case of India, the cumulative emissions amount to 180 $GtCO_2$, which corresponds to an almost 50% increase relative to TAX-30. For OAS, the effect of delay is less pronounced because the bulk of future emission growth in the no-policy scenarios is projected to occur after 2020. In the delay2020 case, the global CO_2 emissions in 2020 are 7% higher than in the corresponding TAX-30 case, and the resulting increase of cumulative global CO_2 emissions until 2100 amounts to 240 $GtCO_2$. The 10-year delay of climate policy of Asian countries has a

[5] One has to keep in mind that the effect of delaying climate policy is influenced by the assumption in ReMIND that power plants cannot be retired early.

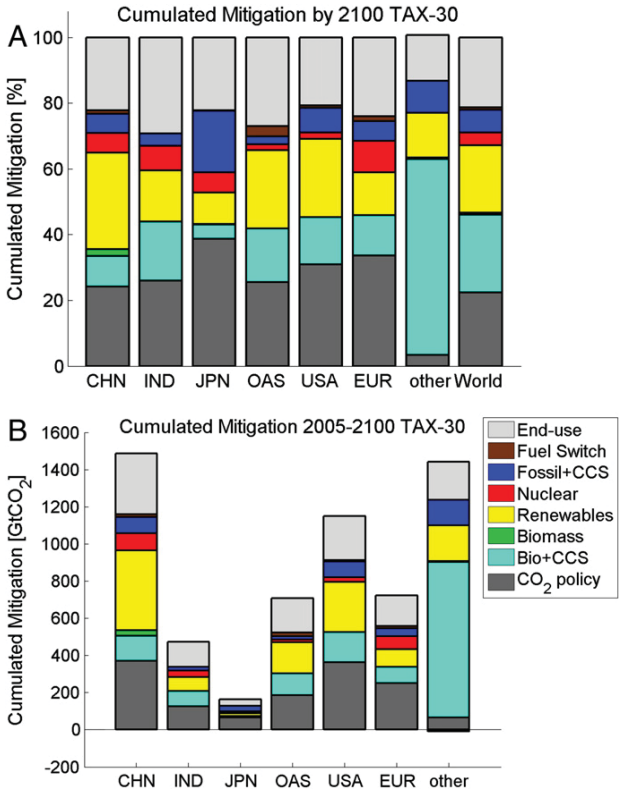


Fig. 6. Cumulated mitigation from 2005 to 2100 in selected model regions, expressed (A) relative to baseline emissions, and (B) in absolute terms.

small but noticeable effect on long term radiative forcing and temperature levels. In particular, it implies an increase in the likelihood of overshooting the 2 °C target to 66% compared to 52% in the TAX-30 scenario (Table 2).

6. Discussion: methodological issues

The analysis of the role of technologies in reducing energy system emissions ranks high on the agenda of climate mitigation research in general and integrated assessment modeling in particular. As discussed in Section 1, different ways of characterizing the role of technologies in for climate change mitigation exist. They can be grouped into (a) analyses of deployment levels, (b) analyses of the cost markups arising from foregoing certain technology options ("knock-off scenarios"), and (c) analysis of mitigation effectiveness, i.e. the quantification of the contribution of technologies to emission reductions. In this paper, we introduced the concept of secondary energy based mitigation shares, which falls into the latter category.

While these three different approaches provide a consistent perspective, they are not equivalent. They assess the role of technologies from different angles, and thus are largely complementary. Studies of deployment levels can inform about technology roadmaps and expansion rates that are consistent with climate stabilization targets. Technology knock-off scenarios give an indication of the degree of indispensability of low carbon technologies, and allow quantifying their strategic economic value. Mitigation shares provide a metric for the contribution of technologies in terms of emission reductions achieved, i.e. the realized mitigation potentials. Deployment levels of mitigation technologies, by themselves, do not provide the full information about emission reductions induced, since these depend on the emissions of production capacities replaced. Thus the added value of mitigation shares as a diagnostic tool lies in weighting the expansion of each technology with the emission reductions induced by replacing secondary energy production capacities that would have been utilized in the absence of climate policy, thus synthesizing information about deployment levels in the policy case relative to the baseline, as well as substitutions within the energy system.

The most critical drawback in the use of mitigation contributions is the methodological complexity and ambiguity. A number of different approaches exist for quantifying emission reduction contributions of technologies. This ambiguity in methodology leads to uncertainty about the appropriate decomposition of emission reductions. In our view, the secondary energy based mitigation shares presented here are superior to existing approaches based on primary energy deployment, chiefly because substitutions of fossil-based technologies by low-carbon alternatives are traced at the finest level resolved by the model, and because they remove the ambiguity related to primary energy accounting. However, as discussed in Section 3.2, the treatment of substitutions between different final energy carriers remains ambiguous in this framework.

Several other important caveats and limitations remain: (a) in view of the complex system dynamics within the energy system, it is not possible to construct alternative mitigation scenarios by recombining individual mitigation shares. The decomposition of emission reductions into mitigation fractions is thus only a diagnostic tool for the analysis of individual climate change mitigation scenarios. This caveat is particularly important for the communication of results to stakeholders and policy-makers. (b) The method only accounts for expansion of mitigation technologies beyond baseline levels. Thus it tends to obscure the role of low-carbon technologies with substantial deployment levels in the reference scenario, e.g. nuclear and wind power. (c) The calculation of secondary energy based mitigation shares is rather complex and needs to be tailor-made to the representation of the energy supply and demand structure that is specific to each individual model. The model-dependence of the decomposition methodology limits its applicability for comparisons across models. Further research is required to explore how different energy system representations affect the outcome of the decomposition analysis.

7. Summary and conclusion

We have described the results of a reference and several climate policy scenario runs conducted with ReMIND-R. The focus of our analysis was on the economic mitigation potential of technologies, with a special focus on Asia.

A number of important policy-relevant conclusions emerge from our analysis: Firstly, we find that Asia plays a pivotal role in the global efforts to achieve climate stabilization. Asia currently accounts for almost two fifth of global emissions, and its share is projected to grow further, both in the reference and the climate policy scenarios. Clearly, without involvement of Asian countries, ambitious climate targets cannot be reached. Reconciling the legitimate priorities of Asian developing countries in terms of development and economic prosperity with the requirements of global climate change mitigation requires a substantial deviation from current emission trends and large-scale deployment of low-carbon technologies.

On the global scale, we find biomass in combination with CCS, other renewables, and the reduction of energy demand to offer the largest potential for economic CO_2 emission reductions. Nuclear and fossil CCS also contribute substantially to emission reductions, particularly in the medium term. We find substantial differences in decarbonization of different final energy types. While renewables, nuclear and CCS offer ample opportunities for reducing emissions from electricity supply, the mitigation options for non-electric energy demand represented in ReMIND-R (geothermal heat pumps, bioenergy, and price-induced improvements of energy intensity) only have limited reduction potential. Consequently, much larger emission reductions are realized in the power sector, and the bulk

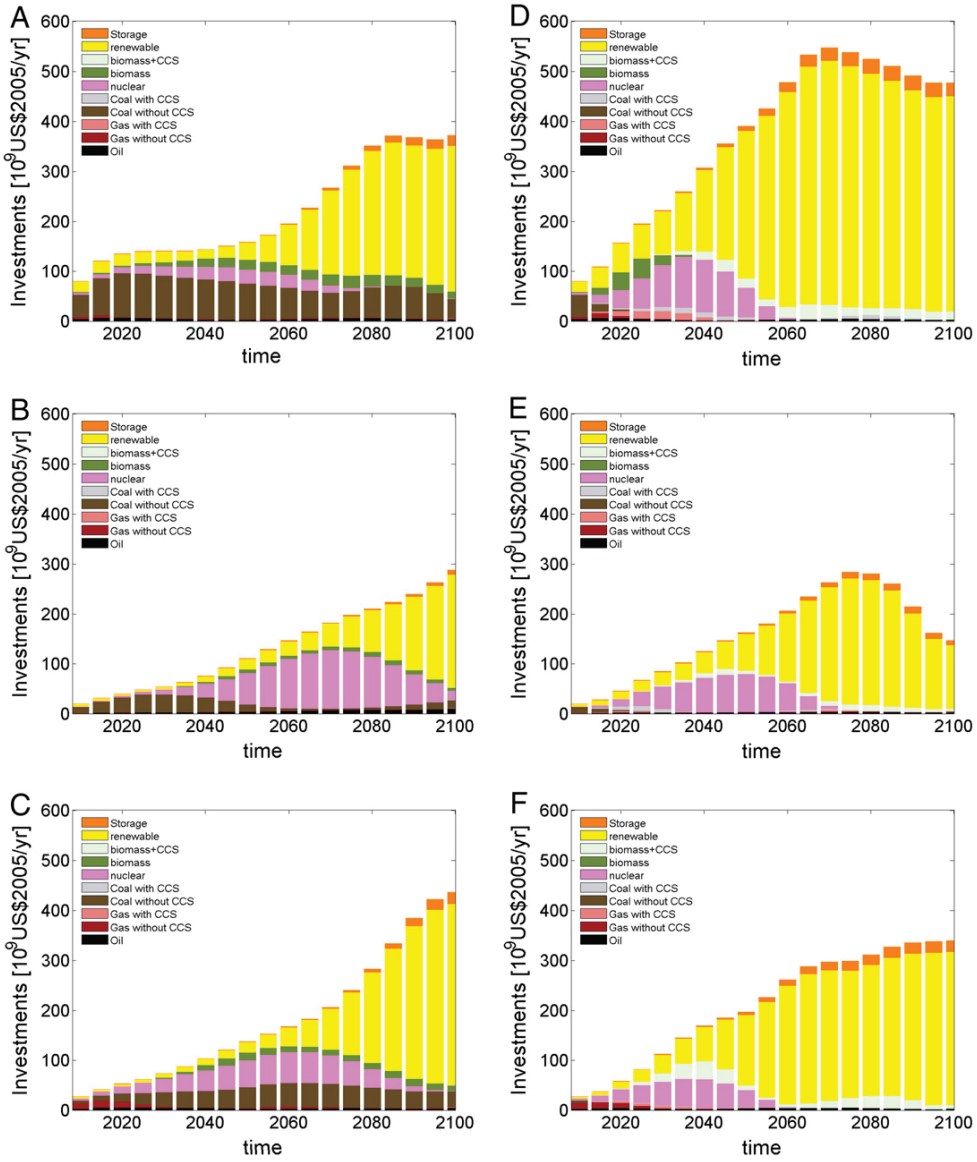


Fig. 7. Investments into power generation capacities for China (top), India (middle) and OAS (bottom), for the reference case (left) and the TAX-30 climate policy scenario (right).

of residual emissions originates from the provision of transport fuels and heat energy supply. This result is in line with the findings of the RECIPE project (Luderer et al., in press), and suggests that the further development of relevant mitigation options for non-electric energy demand (such as electric mobility, the thermal insulation of buildings, and bioenergy use) are of crucial importance for the cost and achievability of low stabilization targets.

Regional differences in the role of mitigation technologies can emerge from three different factors: (a) supply-side differences in fossil and renewable energy resource endowments; (b) demand-side differences in the current structure and the future development of final energy use; and (c) differences in technology factors, such as capital costs, labor costs, and the policy environment, e.g. due to subsidies, regulation, and public acceptance. In our scenarios, differences in resource endowments result in considerable regional differences in technology deployment. While the biomass resource potential and fossil fuel resources are limited in Asia, other renewables are an important long-term mitigation option for China, other developing Asia, and, to a lesser extent, India. In the medium term, nuclear contributes sizably as a bridging technology under climate policy. So far, systematic studies of the effect of structural changes in energy end use, as well as the effect of differences in technology factors are missing. Such analyses should be a priority for further research.

Finally, our results emphasize the long-term benefits of early implementation of climate policy. Many countries in Asia have already adopted climate policy measures. We performed a stylized analysis that contrasts the scenario with immediate and globally coordinated climate policy to a scenario of delayed participation of Asian developing countries. Our results demonstrate that early adoption of climate policy does not only result in near-term emission reductions, but also avoids lock-in into carbon intensive infrastructure and thus leads to a much higher long-term mitigation potential, in particular in China and India.

Acknowledgments

We would like to thank the participants of the AME meeting in Xian as well as two anonymous reviewers for their comments on this work, which helped to improve the methodological framing of

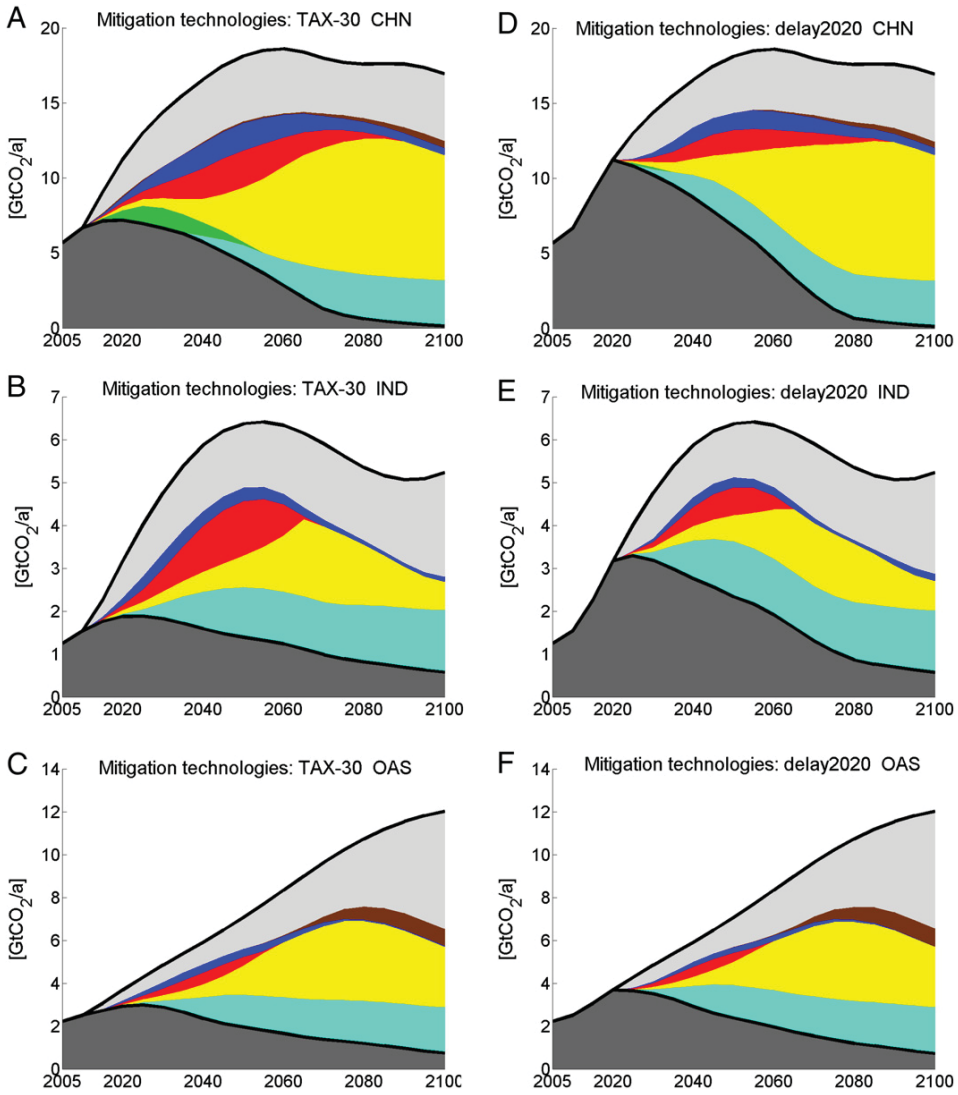


Fig. 8. Emission reductions for China (left), India (middle), and other developing Asia (OAS, right) in response to the carbon taxation for the TAX-30 scenario (upper row) and the delay2020 scenario (lower row). Same color code as in Fig. 1.

this paper. The participation of the ReMIND team in the AME project was supported by EuropeAid under the Climate Policy Outreach (CPO) project.

References

Ang, B., 2004. Decomposition analysis for policymaking in energy: which is the preferred method? Energy Policy 32 (9), 1131–1139 http://www.sciencedirect.com/science/article/pii/S0301421503000764.

Bauer, N., Edenhofer, O., Kypreos, S., 2008. Linking energy system and macroeconomic growth models. Comput. Manag. Sci. 5 (1), 95–117 (February).

Bosetti, V., Carraro, C., Tavoni, M., 2009. A chinese commitment to commit: can it break the negotiation stall? Clim. Chang. 97, 297–303 http://dx.doi.org/10.1007/s10584-009-9726-8. http://dx.doi.org/10.1007/s10584-009-9726-8.

Calvin, K., Edmonds, J., Bond-Lamberty, B., Clarke, L., Kim, S.H., Kyle, P., Smith, S.J., Thomson, A., Wise, M., 2009. 2.6: Limiting climate change to 450 ppm CO_2 equivalent in the 21st century. Energy Econ. 31 (Supplement 2), S107–S120 Dec.

Chen, W., 2005. The costs of mitigating carbon emissions in china: findings from China MARKAL-MACRO modeling. Energy Policy 33 (7), 885–896 (May, http://www.sciencedirect.com/science/article/pii/S030142150300315X).

Chen, W.Y., Wu, Z.X., He, J.K., Gao, P.F., Xu, S.F., 2007. Carbon emission control strategies for china: a comparative study with partial and general equilibrium versions of the china markal model. Energy 32 (1), 59–72 (Jan.).

Clarke, L., Edmonds, J., Krey, V., Richels, R., Rose, S., Tavoni, M., 2009. International climate policy architectures: overview of the EMF-22 international scenarios. Energy Econ. 31 (Supplement 2), S64–S81 (international, U.S. and E.U. Climate Change Control Scenarios: Results from EMF 22).

Edenhofer, O., Knopf, B., Barker, T., Baumstark, L., Bellevrat, E., Château, B., Criqui, P., Isaac, M., Kitous, A., Kypreos, S., Leimbach, M., Lessmann, K., Magné, B., Scrieciu, S., Turton, H., van Vuuren, D.P., 2010. The economics of low stabilization: model comparison of mitigation strategies and costs. Energy J. 31.

Edmonds, J., Wilson, T., Rosenzweig, R., 2000. A Global Energy Technology Strategy Project Addressing Climate Change: an Initial Report an International Public-Private Collaboration. Joint Global Change Research Institute, College Park, MD. http://www.globalchange.umd.edu/data/gtsp/docs/GTSP-indfind.pdf.

EPRI, 2007. The power to reduce CO_2 emissions? The Full Portfolio. EPRI Discussion Paper Palo Alto, CA. http://mydocs.epri.com/docs/CorporateDocuments/AboutEPRI/DiscussionPapercbl.pdf.

Fisher, B., Nakicenovic, N., Alfsen, K., J.C.M., de la Chesnaye, F., Hourcade, J.-C., Jiang, K., Kainuma, M., Rovere, E.L., Matysek, A., Rana, A., Riahi, K., Richels, R., Rose, S., van Vuuren, D., Warren, R., 2007. Climate change 2007: mitigation. Contribution of Working Group III to the Fourth Assessment Report of the IPCC. Cambridge University Press, Cambridge. Ch. Issues related to mitigation in the long term context.

IEA, 2007a. Energy Balances of non-OECD Countries. International Energy Agency, Paris.
IEA, 2007b. Energy Balances of OECD Countries. International Energy Agency, Paris.
IEA, 2010. World Energy Outlook 2010. International Energy Agency, Paris.
IPCC, 2007. Climate change 2007: synthesis report. Tech. rep., Intergovernmental Panel on Climate Change. http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf.
IPCC, 2011. Special report renewable energy sources and climate change mitigation. Intergovernmental Panel on Climate Change. Cambridge University Press.
Jakob, M., Luderer, G., Steckel, J., Tavoni, M., Monjon, S., 2012. Time to act now? assessing the costs of delaying climate measures and benefits of early action. Clim. Chang. 114 (1), 79–99 http://dx.doi.org/10.1007/s10584-011-0128-3.
Jiang, K., Hu, X., 2006. Energy demand and emissions in 2030 in china: scenarios and policy options. Environ. econ. policy stud. 7, 233–250.
Jiang, K., Masui, T., Morita, T., Matsuoka, Y., 2000. Long-term ghg emission scenarios for asia-pacific and the world. Technol. Forecast. Soc. Chang. 63 (2–3), 207–229 (Feb., http://www.sciencedirect.com/science/article/pii/S0040162599001109).
Kainuma, M., Matsuoka, Y., Morita, T. (Eds.), 2003. Asia-Pacific Integrated Modeling. Springer, Tokyo.
Knopf, B., Luderer, G., Edenhofer, O., 2011. Exploring the feasibility of low stabilization target. WIREs Clim. Chang. 1, 617–626 http://dx.doi.org/10.1002/wcc.124.
Krey, V., Clarke, L., 2011. Role of renewable energy in climate mitigation: a synthesis of recent scenarios. Clim. Pol. http://dx.doi.org/10.1080/14693062.2011.579308.
Krey, V., Riahi, K., 2009. Implications of delayed participation and technology failure for the feasibility, costs, and likelihood of staying below temperature targets—greenhouse gas mitigation scenarios for the 21st century. Energy Econ. 31 (Supplement 2), S94–S106 (Dec., http://www.sciencedirect.com/science/article/pii/S0140988309001170).
Leimbach, M., Bauer, N., Baumstark, L., Edenhofer, O., 2010. Mitigation costs in a globalized world: climate policy analysis with REMIND-R. Environ. Model. Assess. 15, 155–173 http://dx.doi.org/10.1007/s10666-009-9204-8.
Lightfoot, H.D., 2007. Understand the three different scales for measuring primary energy and avoid errors. Energy 32 (8), 1478–1483 (Aug.).
Luderer, G., Bosetti, V., Jakob, M., Leimbach, M., Steckel, J., Waisman, H., Edenhofer, O., 2012. The economics of decarbonizing the energy system — results and insights from the RECIPE model intercomparison. Clim. Chang. 114 (1), 9–37 http://dx.doi.org/10.1007/s10584-011-0105-x.
Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., 2010. Description of the ReMIND-R model. Technical Report, Potsdam Institute for Climate Impact Research. http://www.pik-potsdam.de/research/research-domains/sustainable-solutions/models/remind/REMIND_Description_June2010_final.pdf.
Macknick, J., 2011. Energy and CO_2 emission data uncertainties. Carbon Manag. 2 (2), 189–205.
Manne, A., Mendelsohn, R., Richels, R., 1995. MERGE: a model for evaluating regional and global effects of GHG reduction policies. Energy Policy 23 (1), 17–34 (Jan., http://www.sciencedirect.com/science/article/pii/030142159590763W).
McKinsey & Company, 2009. Pathways to a low carbon economy – version 2 of the global greenhouse gas abatement cost curve. Tech. rep., McKinsey & Company. https://solutions.mckinsey.com/ClimateDesk/default.aspx
Meinshausen, M., Meinshausen, N., Hare, W., Raper, S.C.B., Frieler, K., Knutti, R., Frame, D.J., Allen, M.R., 2009. Greenhouse-gas emission targets for limiting global warming to 2°C. Nature 458 (7242), 1158–1162 (Apr.).
NEA, 2009. Uranium 2003: Resources, Production and Demand (Tech. rep) Nuclear Energy Agency.
Nordhaus, W., Nakicenovic, N., 2011. Special issue on the economics of technologies to combat global warming. In: Nordhaus, W., Nakicenovic, N. (Eds.), Energy Economics, Volume 33 (Issue 4).
Nordhaus, W.D., Yang, Z., 1996. A regional dynamic general-equilibrium model of alternative climate-change strategies. Am. Econ. Rev. 86 (4), 741–765 (Sep.).
Pacala, S., Socolow, R., 2004. Stabilization wedges: solving the climate problem for the next 50 years with current technologies. Science 305 (5686), 968–972.
Placet, M., Humphreys, K., Mahasenan, N.M., 2004. Climate Change Technology Scenarios: Energy, Emissions and Economic Implications. Pacific Northwest National Laboratory, Richland, Washington.
Raupach, M.R., Marland, G., Ciais, P., Le Quere, C., Canadell, J.G., Klepper, G., Field, C.B., 2007. Global and regional drivers of accelerating CO_2 emissions. Proc. Natl. Acad. Sci. 104 (24), 10288–10293 (Jun).
Riahi, K., Grübler, A., Nakicenovic, N., 2007. Scenarios of long-term socio-economic and environmental development under climate stabilization. Technol. Forecast. Soc. Chang. 74 (7), 887–935 (Sep.).
Riahi, K., Roehrl, R.A., 2000. Greenhouse gas emissions in a dynamics-as-usual scenario of economic and energy development. Technol. Forecast. Soc. Chang. 63 (2–3), 175–205 http://dx.doi.org/10.1016/S0040-1625(99)00111-0.
Richels, R., Blanford, G., Rutherford, T., 2009. International climate policy: a “second best” solution for a “second best” world? Clim. Chang. 97, 289–296 http://dx.doi.org/10.1007/s10584-009-9730-z.
Shukla, P.R., Dhar, S., Mahapatra, D., 2008. Low-carbon society scenarios for india. Clim. Pol. Volume 8 (Supplement 1), S156–S176 (21).
Steckel, J.C., Jakob, M., Marschinski, R., Luderer, G., 2011. From carbonization to decarbonization?—past trends and future scenarios for China's CO_2 emissions. Energy Policy 39 (6), 3443–3455 (Jun.).
Trieb, F., Schillings, C., O'Sullivan, M., Pregger, T., Hoyer-Klick, C., 2009. Global potential of concentrating solar power. Conference Proceedings, SolarPACES 2009. http://www.dlr.de/tt/en/Portaldata/41/Resources/dokumente/institut/system/projects/reaccess/DNI-Atlas-SP-Berlin_20090915-04-Final-Colour.pdf.
UNFCCC, 2012. Copenhagen Accord. United Nations Framework convention on Climate Change. http://unfccc.int/resource/docs/2009/cop15/eng/l07.pdf.
van Vuuren, D., den Elzen, M., Lucas, P., Eickhout, B., Strengers, B., van Ruijven, B., Wonink, S., van Houdt, R., 2007. Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs. Clim. Chang. 81, 119–159.

FURTHER READING

Calvin, K., this issue. AME Synthesis.

Secondary Energy Based Mitigation shares.

Supplementary Material for the Paper
"Asia's Role in Mitigating Climate Change:
A Technology and Sector Specific Analysis with ReMIND-R"

Gunnar Luderer, Robert C. Pietzcker, Elmar Kriegler,
Markus Haller, Nico Bauer

December 21, 2011

This document provides supplementary information on the abovementioned article. It contains a detailed description of the approach used to calculate mitigation shares and proofs that the approach is complete in the sense that the sum of all individual shares is equal to the difference between baseline and policy emissions.

1 Basic concept

The basic rationale is to attribute emission reductions induced by climate policy to individual technologies by tracking the substitution between different technology pathways for the provision of secondary energy. By considering region, time period, and secondary energy type individually, the calculation is performed at the highest possible resolution represented in the ReMIND model.

More formally, we base our method on the following requirements, or *axioms*:

(A1) The sum of all individual technology shares shall equal the difference between baseline and policy emissions for each time step and region.

(A2) For each time step, region and secondary energy carrier, the abatement credit (i.e., the emission intensity per unit of secondary energy production capacity replaced relative to baseline) shall be equal for all technologies with deployment levels higher than in the baseline.

(A3) For each time step, region and secondary energy carrier, the abatement credit for reductions of end-use shall be equal to that of secondary energy producing technologies.

(A4) For each time step and region, the mitigation share of technologies with deployment levels lower than in the baseline shall be zero.

These axioms are rather intuitive. (A1) demands that the decomposition of emissions abatement into shares be complete. (A2) and (A3) ensure that all technologies that produce the same secondary energy carrier as well as end-use efficiency are credited equal for the replacement of CO2-emitting production capacities that would have existed in the baseline. Axiom (A4) ensures that none of the emission reductions are attributed to "dirty" technologies for being deployed at lower levels than in the baseline.

2 Algorithmic Implementation

Based on the above axioms, secondary-energy based mitigation shares can be constructed in a straight-forward way. It is essential that the method is applied for each time step and region individually. However, for the sake of better readability the indices for region r and time t are omitted in the following. The routine is composed of the following distinct steps:

1. For each technology i and secondary energy type j, calculate the difference of production between baseline and policy scenario ΔS_{ij}:

$$\Delta S_{ij} = S_{ij}^{\text{pol}} - S_{ij}^{\text{bau}} \tag{1}$$

2. Calculate emission intensities for each technology i producing secondary energy carrier j:

$$\varepsilon_{ij}^{\text{bau,pol}} = \frac{E_{ij}}{S_{ij}} \tag{2}$$

   In the case of joint production, emissions for each technology are distributed across products according to the relative output shares. Note that the emission intensities in the policy case can be different from those in the baseline, e.g. due to climate-policy induced efficiency improvements or different vintage structures.

3. Calculate abatement credit $\overline{\varepsilon}_j$ as the average emission intensity of replaced production capacities of secondary energy carrier j:

$$\overline{\varepsilon}_j = \frac{\sum_{i:\Delta S_{ij}\leq 0}(E_{ij}^{\text{pol}} - E_{ij}^{\text{bau}})}{\sum_{i:\Delta S_{ij}\leq 0} \Delta S_{ij}} \tag{3}$$

   where the sums run over all technologies with deployment ΔS_{ij} lower than in the baseline. We show in Sec. 4 that this definition of $\overline{\varepsilon}_j$ ensures that axiom (A1) is satisfied – i.e. that the sum of all individual technology shares equals the difference between baseline and policy emissions.

4. For all conversion technologies i that are deployed at higher levels than in the baseline, calculate mitigation contribution M_{ij} for the production of secondary energy carrier j:

$$M_{ij} = \begin{cases} \Delta S_{ij}(\overline{\varepsilon}_j - \varepsilon_{ij}^{\text{pol}}) + S_{ij}^{\text{bau}}(\varepsilon_{ij}^{\text{bau}} - \varepsilon_{ij}^{\text{pol}}) & \text{if } \Delta S_{ij} > 0 \\ 0 & \text{if } \Delta S_{ij} \leq 0 \end{cases} \tag{4}$$

The mitigation contribution is set to zero for technologies with deployment lower than in the baseline. Note that the second component in the sum accounts for changes in the emission intensity of the conversion technology. If the emission intensity is invariant between BAU and policy case, this term vanishes. This is usually the case, since climate policy will result in expansion of low emission technologies.

5. For each secondary energy carrier j, calculate the contribution of adjustments in energy end-use to emission reductions. These terms capture both the reductions in final energy demand and substitutions between end-energy carriers.

$$M_j^{\text{end}} = -\sum_i (S_{ij}^{\text{pol}} - S_{ij}^{\text{bau}})\,\overline{\varepsilon}_j \tag{5}$$

Note that M_j^{end} can become negative if the secondary energy demand j is higher in the policy case than in the baseline. For some of the scenarios considered, we find electrification of energy end use to result in higher electricity consumption than in the baseline, thus yielding a negative end-use share for electricity. In line with intuition, however, this is found to be smaller than the end-use related emission reduction from non-electric end use.

3 Aggregation to sector shares

In the model setting discussed in the paper, the concept described in Sec. 2 results in about 450 mitigation contribution time series M_{ij} – one for each technology and region, plus one end-use share for each energy carrier and region. Fig. 1 gives a graphical representation of these *micro shares*.

The micro shares can be further aggregated across regions, end-use sectors, or technology groups (see Fig. 2). Table 1 shows the composition of the technology groups and their contribution to different end-use sectors. Note that the assignment to technology groups is complete; all conventional technologies are part of the *Fuel Switch* group and have a mitigation contribution unequal to zero if they are deployed at higher levels than in the baseline.

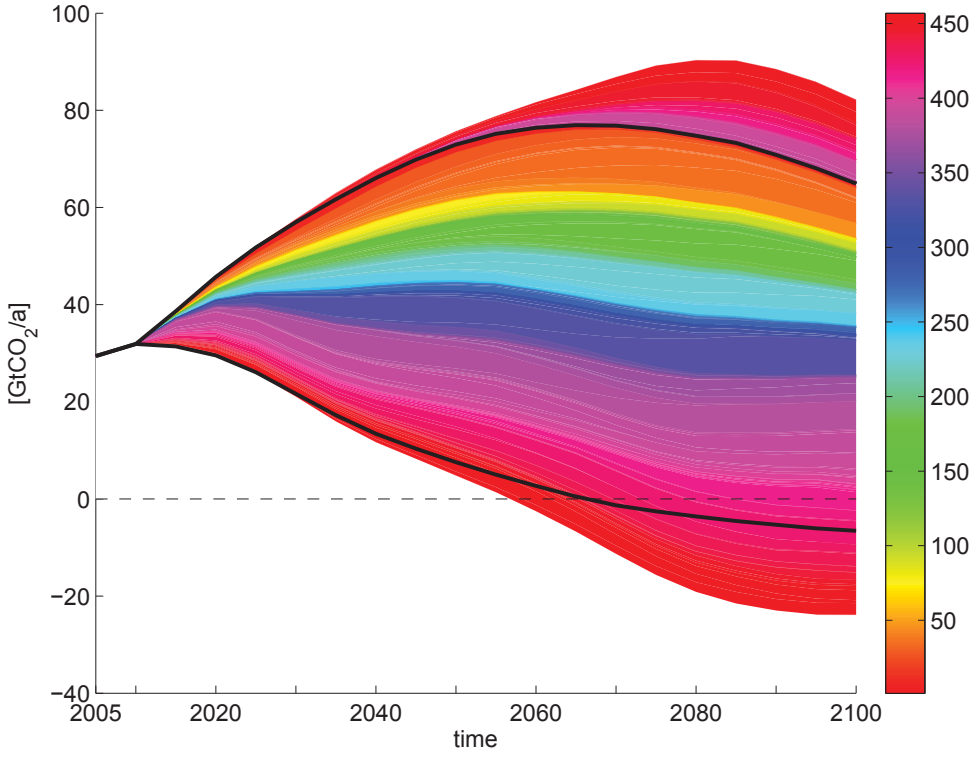


Figure 1: Micro shares: One technology share for each mitigation technology and region, plus one efficiency share for each secondary energy carrier and region, results in a total of about 450 shares.

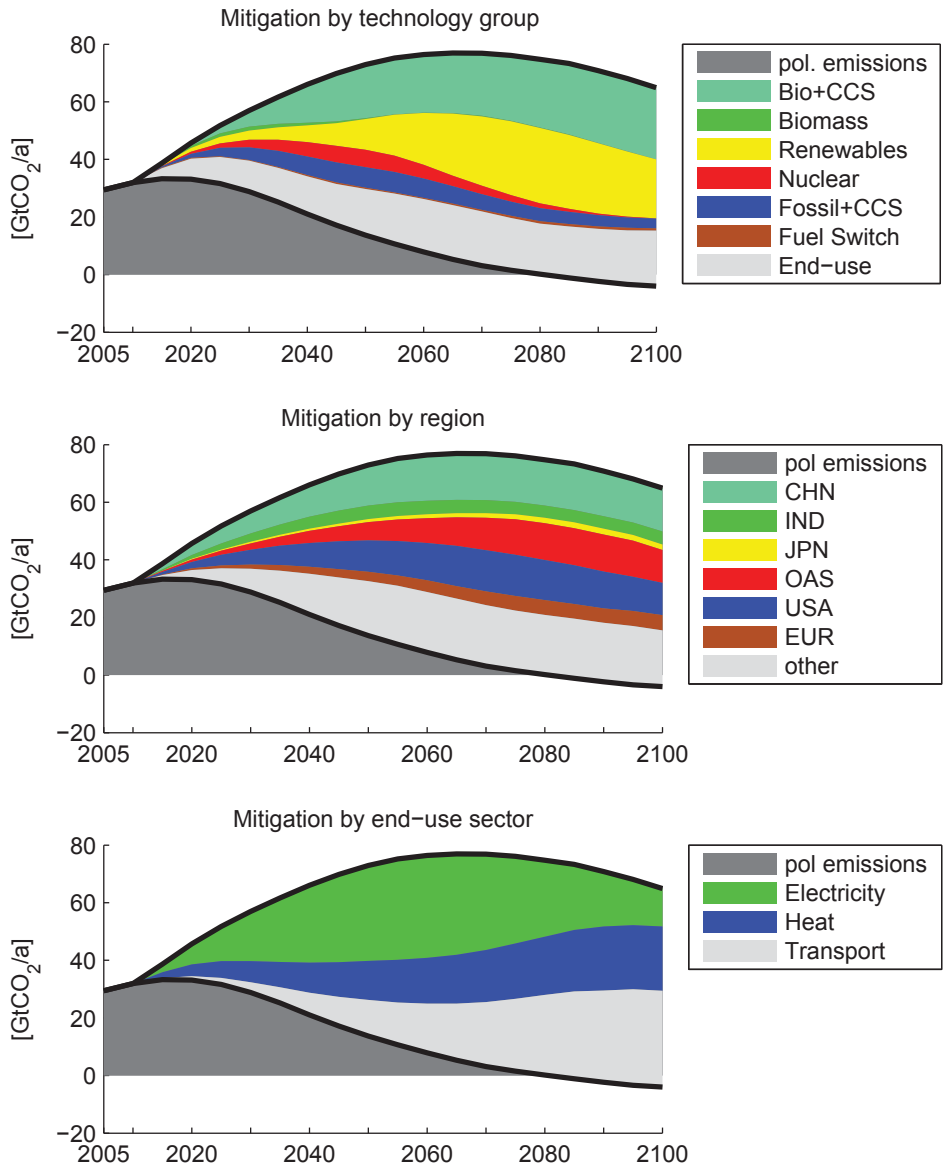


Figure 2: Aggregation of micro shares across technology groups, regions and end-use sectors.

Table 1: Technology groups and their contribution to end-use sectors. PP: power plant, CHP: combined heat and power, CC: combined cycle, IGCC: integrated gasification combined cycle.

	Electricity	Heat	Transport
Renewables	Concentrating Solar Power Solar PV Wind turbine Hydropower Geothermal	Solar thermal Heat pump	
Biomass	Biomass IGCC Biomass CHP	Biomass HP Biomass CHP Biomass gasification Biomass to H_2 Traditional biomass	Biomass to liquid Biomass to H_2
Biomass + CCS	Biomass IGCC + CCS Biomass to liquid + CCS	Biomass to H_2 + CCS	Biomass to H_2 + CCS Biomass to liquid + CCS
Fossil + CCS	Gas CC + CCS Pulverized coal PP + CCS IGCC + CCS Oxfuel PP	Gas to H_2 + CCS Coal to H_2 + CCS	Gas to H_2 + CCS Coal to H_2 + CCS Coal to liquid + CCS
Nuclear	Thermal reactor		
Fuel Switch	Pulverized Coal PP Coal IGCC Gas turbine Gas CC Diesel turbine Coal CHP Gas CHP	Gas HP Gas CHP Gas to H_2 Gas direct Coal HP Coal CHP Coal gasification Coal direct Refinery	Gas to H_2 Coal to H_2 Coal to liquid Refinery

4 Completeness of decomposition

By construction, the secondary energy shares as described in Section 2 fulfill axioms (A2-A4). In the following we proof that algorithm also fulfills axiom (A1), i.e. that the decomposition is complete in the sense that the sum of all technology contributions M_{ij} and the end-use contribution M_j^{eff} is equal to the difference of baseline and policy emissions:

$$M_j = E_j^{\text{bau}} - E_j^{\text{pol}} = \sum_{i:\Delta S_{ij}>0} M_{ij} + M_j^{\text{end}} \tag{6}$$

Inserting equations 4 and 5 into equation 6 and rearranging the resulting terms yields:

$$\begin{aligned}
M_j &= \sum_{i:\Delta S_{ij}>0} M_{ij} + M_j^{\text{end}} && (7)\\
&= \sum_{i:\Delta S_{ij}>0} \left(\Delta S_{ij}(\overline{\varepsilon}_j - \varepsilon_{ij}^{\text{pol}}) + S_{ij}^{\text{bau}}(\varepsilon_{ij}^{\text{bau}} - \varepsilon_{ij}^{\text{pol}})\right) - \overline{\varepsilon}_j \sum_i \Delta S_{ij} && (8)\\
&= \overline{\varepsilon}_j \left(\sum_{i:\Delta S_{ij}>0} \Delta S_{ij} - \sum_i \Delta S_{ij}\right) + \sum_{i:\Delta S_{ij}>0} \left(S_{ij}^{\text{bau}}(\varepsilon_{ij}^{\text{bau}} - \varepsilon_{ij}^{\text{pol}}) - \varepsilon_{ij}^{\text{pol}} \Delta S_{ij}\right) && (9)\\
&= -\overline{\varepsilon}_j \sum_{i:\Delta S_{ij}\leq 0} \Delta S_{ij} + \sum_{i:\Delta S_{ij}>0} \left(\varepsilon_{ij}^{\text{pol}} S_{ij}^{\text{bau}} - \varepsilon_{ij}^{\text{pol}} S_{ij}^{\text{pol}} + \varepsilon_{ij}^{\text{bau}} S_{ij}^{\text{bau}} - \varepsilon_{ij}^{\text{pol}} S_{ij}^{\text{bau}}\right) && (10)\\
&= -\sum_{i:\Delta S_{ij}\leq 0} (E_{ij}^{\text{pol}} - E_{ij}^{\text{bau}}) + \sum_{i:\Delta S_{ij}>0} (E_{ij}^{\text{bau}} - E_{ij}^{\text{pol}}) && (11)\\
&= E_j^{\text{bau}} - E_j^{\text{pol}} && (12)
\end{aligned}$$

As shown, the decomposition of emission reductions into technology and end-use shares is complete for each secondary energy carrier j, and thus also for the total emissions.

5 Sensitivity analysis: Alternative calculation algorithms

As mentioned in Section 3.2 of the main paper, the used algorithm to calculate mitigation shares cannot differentiate between actual end-use reductions and substitutions between secondary energy carriers used for the same final energy type. While this usually does not matter for the results, there are a few instances within ReMIND where this produces counterintuitive results, the most important being the production of hydrogen (H_2) from BioCCS in strong mitigation scenarios.

H_2 is used to supply both heat and transport energy, and in baseline scenarios it is mostly produced from coal, thus having high specific emissions. In policy scenarios, it is mostly produced from BioCCS, resulting in negative emissions. It is therefore used much more strongly than in baseline scenarios and replaces other secondary energy carriers like gas (used for heat) or petrol (used for transport).

In the default algorithm, the increased H_2 is registered twofold - once as "additional emissions due to increased H_2 use", which is counted negatively towards the efficency share[1], and once as "reduced emissions due to a different technology", for which BioCCS receives the full credit for decarbonizing this large share of emission-intensive H_2. In the logic of the model, however, H_2 and gas are quite well substitutable (substitution elasticity of 3 within the final energy type heat), so the hydrogen from BioCCS actually replaces gas or petrol and not emission-intensive coal-H_2.

To test how much we possibly over- or underestimate the contributions from energy efficiency, BioCCS and renewables, we developed two alternative calculation methods:

Alternative method 1: Specific emission intensity from policy run The change of the total amount of a secondary energy carrier is credited either with the specific emission intensity of the policy run or zero, depending on which is larger.[2]

Alternative method 2: Linear substitution within one final energy type Each final energy type (heat, electricity, transport) is treated as if the secondary energies used to supply it can substitute each other linearly. Thus, the average specific abatement credit is calculated for the sum of all secondary energy carriers within one final energy type, not individually for each secondary energy. This average specific abatement credit is then used as $\overline{\varepsilon}_j^{\text{bau}}$ in equations (4) and (5) in Section 2 to calculate both the efficiency and the individual technology contributions.

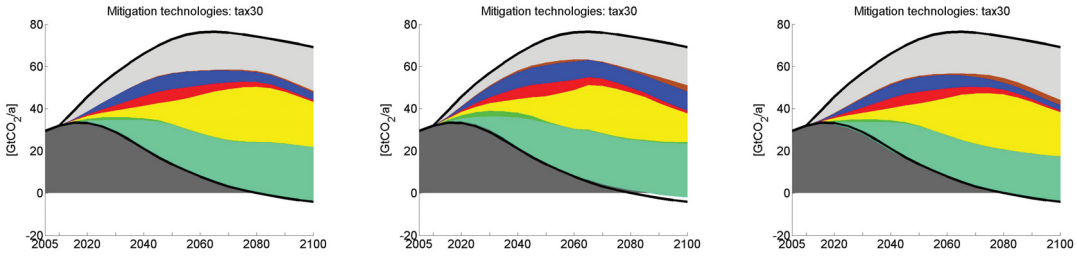
It should be noted that both alternatives require some rescaling of the specific abatement credit used to calculate the technology mitigation shares, else the sum of individual abatement shares does not add up to the total of mitigated emissions.

The results of the alternative algorithms are shown in Figure 3. Although the detailed breakdown of mitigation shares over final energy types and time is influenced by the different algorithms, the general trend of the global mitigation shares is quite similar across all three algorithms. When comparing the differences between the different algorithms for secondary energy based mitigation shares with those of primary energy based mitigation shares as described in Section 6, we conclude that the ambiguities can be significantly reduced by using secondary energy based shares.

Alternative method 1: Specific emission intensity from policy run: This method attributes changes of the total level of a secondary energy carrier with the specific emission intensity of a policy run. Thus, reductions of energy use have a much smaller positive mitigation contribution. To still cover the full abatement done in this sector, the mitigation contribution of the remaining technology change has to be scaled up accordingly. This leads to the counterintuitive result that the specific emission reduction achieved through a zero-carbon technology is larger than the specific abatement credit for the displaced emission-intensive technology.

[1] To calculate the efficiency share, the total change in secondary energy use is weighted with the specific emissions of the displaced baseline technologies.

[2] Allowing negative specific abatement credits for efficiency would lead to the strongly counterintuitive result that all the credit of the negative BioCCS emissions go to end-use efficiency for *increasing* the use of *negative emission energy*.



(a) Default algorithm (b) Spec. em. factor from policy (c) Linear substitution

Figure 3: Global mitigation shares calculated with different algorithms: (a) default, (b) efficiency is weighted with the specific emission intensity of the policy run, (c) as default, but all secondary energy carriers within one final energy type are treated as one energy carrier.

An example may help to illustrate this problem: In a baseline run, 10 EJ of a secondary energy carrier are used, the specific emission intensity of the supplying technology is 1 GtC/EJ, thus total emissions from this secondary energy carrier are 10 GtC. In the policy run, only 5 EJ of this secondary energy carrier are used, and these 5 EJ are completely decarbonized through a zero-emission technology, thus total emissions are 0 GtC. Using the alternative method 1, the efficiency share would then be zero, as the specific emission intensity of the policy run is zero. Thus, the 10 GtC abatement would be attributed to the 5 EJ of clean energy, resulting in a specific mitigation credit of the zero-carbon technology of 2 GtC/EJ - more than was initially emitted in the baseline.

This effect is strongest in the transport sector, where liquid transport fuels produced from coal are reduced and replaced by liquid fuels from coal with CCS. As the mitigation contribution from demand reduction is weighted less strongly, the fossil+CCS option increases accordingly. Several smaller changes in the two other final energy types where the efficiency share increases at the cost of the renewable contribution lead to an aggregated picture as seen in Figure 3b: the Fossil+CCS mitigation share gains, mostly at the cost of the shares from renewables and energy efficiency.

Alternative method 2: Linear substitution within one final energy type: The advantage of this method is that it partly overcomes the problem of similar secondary energy carriers substituting each other within one final energy type by assuming they substitute linearly and netting out their individual level changes. It thus manages to better differentiate real efficiency gains (reduced total energy use of one final energy type) from substitutions between energy carriers.

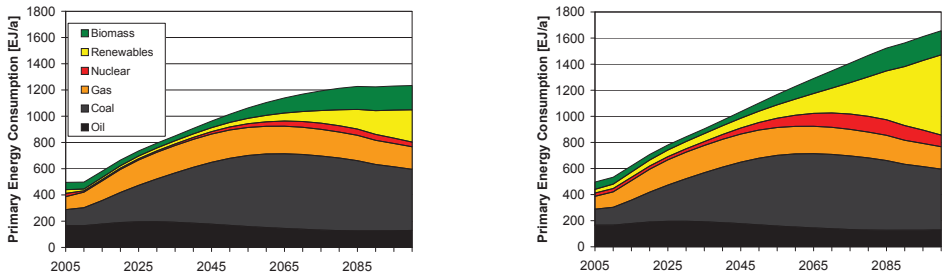
The main drawback is that the algorithm is not exact in representing the substitution within the model as it assumes linear substitution within one end-use type. In contrast, secondary energy carriers substitute non-linearly via a constant elasticity of substitution function in ReMIND. Therefore, the algorithm requires a small ex-post-rescaling of the specific abatement credit for each final energy type.

6 Primary Energy vs. Secondary Energy Accounting

To our knowledge, most existing approaches for the calculation of mitigation shares from integrated assessment scenarios are based on primary energy accounting. As elaborated in Section 3 of the main paper, this is problematic for two reasons: (a) substitutions in the model occur mostly on the secondary level (e.g. one unit of nuclear electricity for one unit of coal-based electricity), rather than on the primary level; and (b) ambiguities in primary energy accounting translate directly into ambiguities in the calculation of mitigation shares.

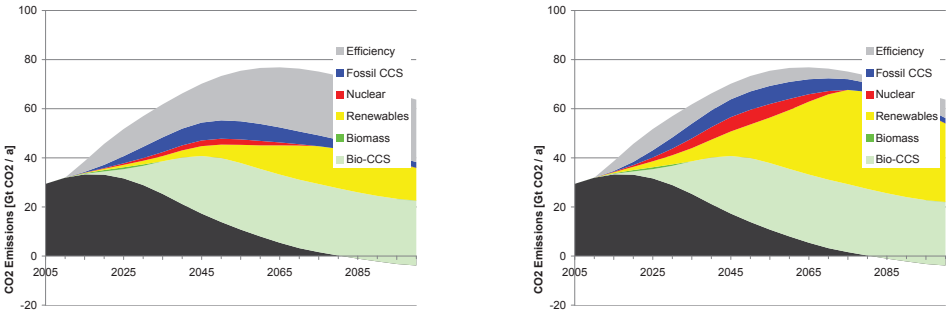
In order to illustrate the second point, we present PE mixes based on (a) the direct equivalent accounting method, and (b) the substitution method. In direct equivalent accounting, one unit of secondary energy production from non-combustible primary energy (in particular nuclear and non-biomass renewables) is accounted as one unit of primary energy. The substitution method, by contrast, reports primary energy from non-combustible sources as if it had been substituted for combustible energy. See IPCC (2011, Appendix II) for a detailed discussion of primary energy accounting. The different methods result in a factor of three difference in primary energy accounting of fossils and non-biomass renewables. As shown in Figure 4, the difference between PE accounting methods is substantial, in particular for mitigation scenarios with high penetration of non-biomass renewables and nuclear.

The ambiguity in primary energy accounting translates directly to ambiguity in the calculation of primary energy based mitigation shares: As illustrated in Figure 5, for the substitution method, mitigation shares of nuclear and non-biomass renewables are much larger than in the case of direct equivalent accounting, while efficiency assumes is much higher for direct equivalent accounting compared substitution method. An important advantage of the methodology of secondary energy energy based mitigation shares (Figure 2) is that the ambiguity arising from primary energy accounting is removed.



(a) direct equivalent accounting (b) substitution method

Figure 4: Primary energy supply for the ReMIND TAX-30 scenario, (a) based on direct equivalent accounting, and (b) based on substitution method.



(a) direct equivalent accounting (b) substitution method

Figure 5: Illustrative primary energy mitigation shares for the ReMIND TAX-30 scenario based on a simple calculation using an ad-hoc method. The use of (a) direct equivalent accounting, or (b) the substitution method has a strong effect on the resulting mitigation shares.

Chapter 3

The role of renewable energy in climate stabilization: results from the EMF27 scenarios*

Gunnar Luderer
Volker Krey
Katherine Calvin
James Merrick
Silvana Mima
Robert Pietzcker
Jasper Van Vliet
Kenichi Wada

*published in *Climatic Change* as Luderer, G., Krey, V., Calvin, K., Merrick, J., Mima, S., Pietzcker, R., Vliet, J.V., Wada, K., (2014) "The role of renewable energy in climate stabilization: results from the EMF27 scenarios". Climatic Change 1–15
dx.doi.org/10.1007/s10584-013-0924-z

Climatic Change
DOI 10.1007/s10584-013-0924-z

The role of renewable energy in climate stabilization: results from the EMF27 scenarios

Gunnar Luderer · Volker Krey · Katherine Calvin · James Merrick · Silvana Mima · Robert Pietzcker · Jasper Van Vliet · Kenichi Wada

Received: 3 December 2012 / Accepted: 31 August 2013
© Springer Science+Business Media Dordrecht 2013

Abstract This paper uses the EMF27 scenarios to explore the role of renewable energy (RE) in climate change mitigation. Currently RE supplies almost 20 % of global electricity demand. Almost all EMF27 mitigation scenarios show a strong increase in renewable power production, with a substantial ramp-up of wind and solar power deployment. In many scenarios, renewables are the most important long-term mitigation option for power supply. Wind energy is competitive even without climate policy, whereas the prospects of solar photovoltaics (PV) are highly contingent on the ambitiousness of climate policy. Bioenergy is an important and versatile energy carrier; however—with the exception of low temperature heat—there is less scope for renewables other than biomass for non-electric energy

This article is part of the Special Issue on "The EMF27 Study on Global Technology and Climate Policy Strategies" edited by John Weyant, Elmar Kriegler, Geoffrey Blanford, Volker Krey, Jae Edmonds, Keywan Riahi, Richard Richels, and Massimo Tavoni.

Electronic supplementary material The online version of this article (doi:10.1007/s10584-013-0924-z) contains supplementary material, which is available to authorized users.

G. Luderer (✉) · R. Pietzcker
Potsdam Institute for Climate Impact Research, Potsdam, Germany
e-mail: luderer@pik-potsdam.de

V. Krey
International Institute for Applied Systems Analysis, Laxenburg, Austria

K. Calvin
Joint Global Change Research Institute, College Park, MD, USA

J. Merrick
Electric Power Research Institute, Palo Alto, CA, USA

S. Mima
PACTE-EDDEN, CNRS, University Grenoble Alpes, Grenoble, France

J. Van Vliet
PBL Netherlands Environmental Assessment Agency, Bilthoven, The Netherlands

K. Wada
Research Institute of Innovative Technology for the Earth, Kyoto, Japan

Published online: 15 October 2013

Climatic Change

supply. Despite the important role of wind and solar power in climate change mitigation scenarios with full technology availability, limiting their deployment has a relatively small effect on mitigation costs, if nuclear and carbon capture and storage (CCS)—which can serve as substitutes in low-carbon power supply—are available. Limited bioenergy availability in combination with limited wind and solar power by contrast, results in a more substantial increase in mitigation costs. While a number of robust insights emerge, the results on renewable energy deployment levels vary considerably across the models. An in-depth analysis of a subset of EMF27 reveals substantial differences in modeling approaches and parameter assumptions. To a certain degree, differences in model results can be attributed to different assumptions about technology costs, resource potentials and systems integration.

1 Introduction

There are multiple technological options for reducing greenhouse gas (GHG) emissions from the energy system. Besides renewable energy sources (RES), nuclear energy and carbon capture and storage (CCS) are important supply-side mitigation options. RES are often praised as the most sustainable source of energy for two reasons. First, RES are, in principle, carbon-free. There are no direct CO_2 emissions associated with the deployment of non-biomass RES. With a few exceptions, e.g. some forms of bioenergy production, life-cycle GHG emissions of RES are much lower than those caused by fossil fuels, even when all the stages of production are accounted for (Sathaye et al. 2011). Second, the defining feature of renewables is that their resource potential does not deplete over time. Moreover, the combined resource potential of all renewables exceeds the current energy demand by at least one order of magnitude (IPCC 2011). Given the constraints on fossil and nuclear fuel availability, and the limited social acceptance of nuclear waste and CO_2 storage, it seems likely that RES will become increasingly important in the long-term, even if climate policies remain weak. On the other hand, future RES deployment may be limited by (a) the competition with other sources of energy, (b) currently high costs, (c) regional heterogeneity of resources (combined with limited transportability) and (d) systems integration challenges. Since there are more options for producing renewable electricity than non-electric energy, the RES contribution to climate change mitigation will also depend on the degree to which end-uses can be electrified, for instance by introducing electric vehicles. A recent IPCC Report provided already a comprehensive overview of the state of scientific knowledge on RES (IPCC 2011) by assessing, inter alia, resource potential, technology development, deployment costs, and potential future deployment levels. A recent meta-assessment of the role of RES in model based climate mitigation scenarios performed for the SRREN (Krey and Clarke 2011) showed a strong expansion of renewable energy (RE) technologies in many scenarios as well as large differences across models.

The EMF27 study (Kriegler et al. 2013) provides a unique framework to further improve our understanding of the role of RES in climate change mitigation. It features a large set of scenarios with harmonized technology assumptions based on a wide ensemble of structurally different, state-of-the art energy-economy-climate and integrated assessment models (IAMs). The goal of this paper is to explore how renewable energy futures depends on climate policy, technology availability and model-specific assumptions. More specifically, we aim to answer the following research questions: (1) What RES deployment levels are consistent with various stabilization levels, and what are the roles of different RES technologies? (2) How can RES contribute to electric and non-electric energy supplies? (3) How

does the availability of RES affect the cost and achievability of climate targets, and can ambitious climate targets be achieved through RE and energy efficiency alone? (4) What are the key model assumptions and uncertainties affecting RE deployment levels in mitigation scenarios?

The overview paper (Kriegler et al. 2013) provides a full description of the EMF27 scenario design. This paper focuses on the following technology variations:

- ***FullTech:*** Default case with full technological availability
- ***LimSW:*** Share of electricity production from wind and solar limited to 20 %, and pessimistic assumptions regarding cost reductions of these energy sources, reflecting technical, economic and institutional challenges associated with the expansion of variable and uncertain electricity generation.
- ***LimBio:*** Primary energy supply from modern biomass limited to 100 EJ/year, reflecting sustainability concerns about strong expansion bioenergy production.
- ***Conv:*** Share of electricity production from wind and solar limited to 20 %, and primary energy supply from modern biomass limited to 100 EJ/year (focus on conventional supply-side options).
- ***EERE:*** Unavailability of CCS, nuclear phase-out, and higher autonomous energy intensity improvement (30–45 % lower baseline final energy demand in 2100 compared to the other scenarios).

Each of these technology variations consider scenarios where atmospheric GHG concentrations are limited to 450 ppm CO_2e by 2100 (temporary overshooting allowed), stabilize at 550 ppm CO_2e (no overshoot allowed), or no climate policy is implemented (baseline).

2 RE deployment pathways

The EMF27 models differ significantly in their representations of RES. First, they include different RE technologies. Table S2.1 in the supplementary material (SM) provides a detailed overview of the RE technologies represented in the models. While some models describe RE technologies with a high level of detail, e.g., by distinguishing between different solar and wind power technologies (TIAM-WORLD, MESSAGE, POLES, GCAM), other models with a stronger macro-economic focus only represent a few generic types of technology. In general, the models represent a wider variety of renewable options in the electricity sector than in the non-electric sector. Second, the models differ in terms of their methodological approaches and parameter assumptions. Differences related to renewable resource potentials, cost assumptions, and the representation of systems integration are particularly relevant. It is important to keep these differences in mind when comparing scenario results.

We find that (a) there is significant scope for an increasing role of RES even in the absence of climate policies, (b) the contribution of RES to energy supply increases strongly with climate policy stringency, (c) there is greater scope for RES use in power supply than in the supply of non-electric energy, and (d) that RE deployment varies considerably across models (Fig. 1a, b). The remainder of this section reviews the renewable energy deployment levels in the EMF27 scenarios without technology constraints and compares these deployment levels to the potentials provided in the literature. Section 3 analyses how RES contribute to electric and non-electric energy supply in various climate change mitigation scenarios. Section 4 examines the relationship between model assumptions and deployment levels for a subset of EMF27 models.

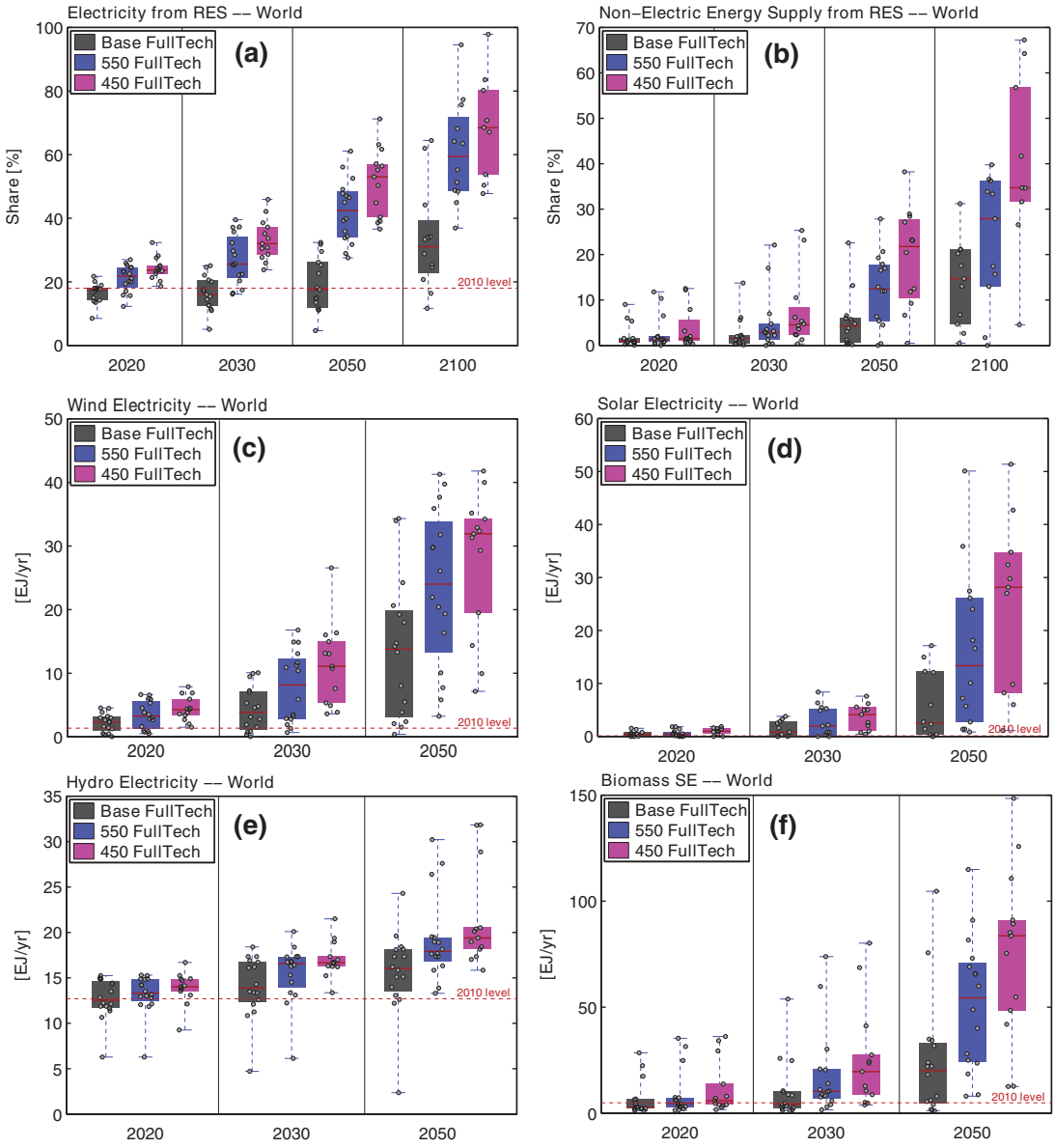


Fig. 1 Secondary energy supply from various RE technology groups in the *Base, 550* and *450 FullTech* scenarios. Red dashed lines indicate 2010 deployment levels based on (IEA 2012). *Boxes* represent 25th-75th percentiles, the *red line* the median, whiskers the full range of results

2.1 Wind power

In 2010, wind turbines produced 1.23 EJ, or 1.6 % of global electricity generation (IEA 2012). The resource potential of wind power is large and uncertain, with several studies citing 70–450 EJ/year (Wiser et al. 2011; Rogner et al. 2012; Turkenburg et al. 2012) as the practical potential and as much as 5,700 EJ/year as the technical potential (GEA).[1] The growth in deployment of wind power in the *Base FullTech* scenario is significant (Fig. 1c),

[1] Wiser et al. (2011) does not use the "practical" and "technical" distinction. Instead, the authors compare potential with "limited constraints" and "more constraints". They estimate 70–450 EJ/year with more constraints and 70–3050 EJ/year with limited constraints.

with most models showing an increase of 5–6 % per year throughout the century. In most models, climate policy results in an acceleration of wind deployment. Six models represent offshore wind power explicitly, and project that its share in total wind power production will increase with increasing wind deployment (Fig S2.2 in the SM).

2.2 Solar power

Although deployment of solar power has shown annual growth rates of almost 40 % over the last 10 years, the current deployment level is still very small, supplying only 0.11EJ/year of electricity in 2010 (IEA). By contrast, the technical potential for solar power is enormous. Turkenburg et al. (2012) estimate the global technical potential for photovoltaics (PV) to range from 1,600–50,000 EJ/year. Similarly, Arvizu et al. (2011) estimate a technical potential of 1,338–14,778 EJ/year for PV and a technical potential of 248–10,791 EJ/year for concentrating solar power (CSP). Solar power production varies significantly across the models, ranging from 0–17 EJ/year in 2050 in the baseline and 0–53 EJ/year in the 450 FullTech scenario (Fig. 1d). While in some models solar power becomes competitive even without climate policies due to technological progress and increasing scarcity of fossil fuels, power supply remains largely based on fossils in other models. Most of the models that represent that level of technology detail project that the share of CSP in solar power increases with increasing total solar deployment (Fig S2.2 in the SM). Climate policy increases solar power generation in most of the models, often substantially. With stringent climate policies in place, solar power assumes a dominant share of electricity production in the 2nd half of the century in some models (MESSAGE, REMIND, TIAM-WORLD).

2.3 Hydropower

Hydro electricity is currently the most significant non-biomass renewable energy source, supplying 12.7 EJ/year or 16 % of the world's electricity in 2010 (IEA 2012). However, the technical potential for hydropower is limited to 50–60 EJ/year (Kumar et al. 2011; Rogner et al. 2012; Turkenburg et al. 2012). As a result, growth in the deployment of hydropower is modest in most models, with climate policies resulting in a moderate increase of relative to baseline levels (Fig. 1e).

2.4 Bioenergy

The global consumption of bioenergy, including traditional biomass, was 53 EJ/year in 2010, which accounts for more than 10 % of total primary energy (IEA). However, bioenergy use is currently dominated by traditional fuel use with low final to useful efficiency. The technical potential for bioenergy in 2050, as estimated by SRREN, is 50–1,000 EJ/year (Chum et al. 2011). Bioenergy is unique for two reasons: (1) its versatility (it can be used to produce liquids, electricity, hydrogen, gases, or heat) and (2) the possibility to create negative emissions when combined with CCS. The future role of biomass to supply modern forms of energy varies significantly across the models and scenarios in the EMF27 study (Fig. 1f and S2.1). In most models, bioenergy is predominantly used for the generation of liquid fuels and electricity. A limited number of models consider heat or gas produced from bioenergy, and often find substantial deployment potentials. Rose et al. (2013) provide an in-depth discussion of bioenergy use in the EMF27 scenarios.

2.5 Other forms of RE use

In addition to wind and solar power, hydro-power and biomass RES can be harvested in a variety of ways. Geothermal energy can be used to produce electricity. However, in those EMF27 models that represent geothermal power production deployment remains relatively small (7 EJ or lower in *FullTech 450*). Aside from biomass, geothermal and solar energy can provide heat. Deployment is substantial in climate policy cases in the few models that represent these technologies, suggesting that they could be of strategic importance for reducing emissions from the buildings sector. SM2.2 provides a more detailed discussion of geothermal power, geothermal heat and solar heat.

3 The relevance of RES for mitigation

This section considers the energy system from a broader perspective in order to examine the relevance of RES for mitigation. The EMF27 scenarios allow us to study how RE deployment levels change with alternative technology assumptions, and how they substitute with alternative energy supply technologies and climate mitigation options. We focus on the 550 ppm climate target because more models report results for technology-constrained scenarios for this stabilization level. By exploring RE deployment for electric and non-electric energy, we analyze in which areas what types of RES contribute most.

3.1 The role of RES in energy supply

The analysis of electricity supplies indicate that renewables can play an important or even dominant role in electricity generation if climate policies are in place. For the *550 FullTech* scenario, the inter-quartile range of RE shares in electricity production is 35–48 % in 2050, and 48–68 % in 2100 (Fig. 1a). Section 4.3 discusses the treatment of systems integration challenges in such scenarios with high shares of variable and uncertain power generation. Models with high overall RE deployment in the power supply, such as REMIND, MESSAGE, TIAM-WORLD and AIM-Enduse tend to have particularly large shares of solar and wind power, while the contribution of hydro-power is more comparable across models (Fig 2a). This is not surprising since the limitations on resource potential are less constraining for solar and wind power than for hydropower. In the scenarios where bioenergy is used for electricity generation, it is mostly deployed with CCS in order to produce net negative emissions. Other models feature limited bioenergy use in the electricity sector. This is often driven by the high value of bioenergy for biofuel production.

Figure 2b shows the conversion pathways for non-electric secondary energy sources. In contrast to electricity, non-electric energy remains dominated by fossil fuels even if climate policies are in place. Biomass is the most important supply-side mitigation option for non-electric energy. It is primarily used to produce liquid biofuel as a substitute for oil. In models that consider liquid biofuel production with and without CCS (GCAM, MESSAGE, REMIND, TIAM-WORLD), production processes with CCS dominate over conversion pathways without CCS in the long-term. Solar-thermal and geo-thermal heating systems are potentially the most relevant non-biomass renewable options for the buildings sector. As pointed out in Section 2.5, only a few EMF27 models consider these options. While deployment can be substantial for individual technologies, non-biomass renewables represent a very small share of non-electric energy sources across all EMF27 scenarios.

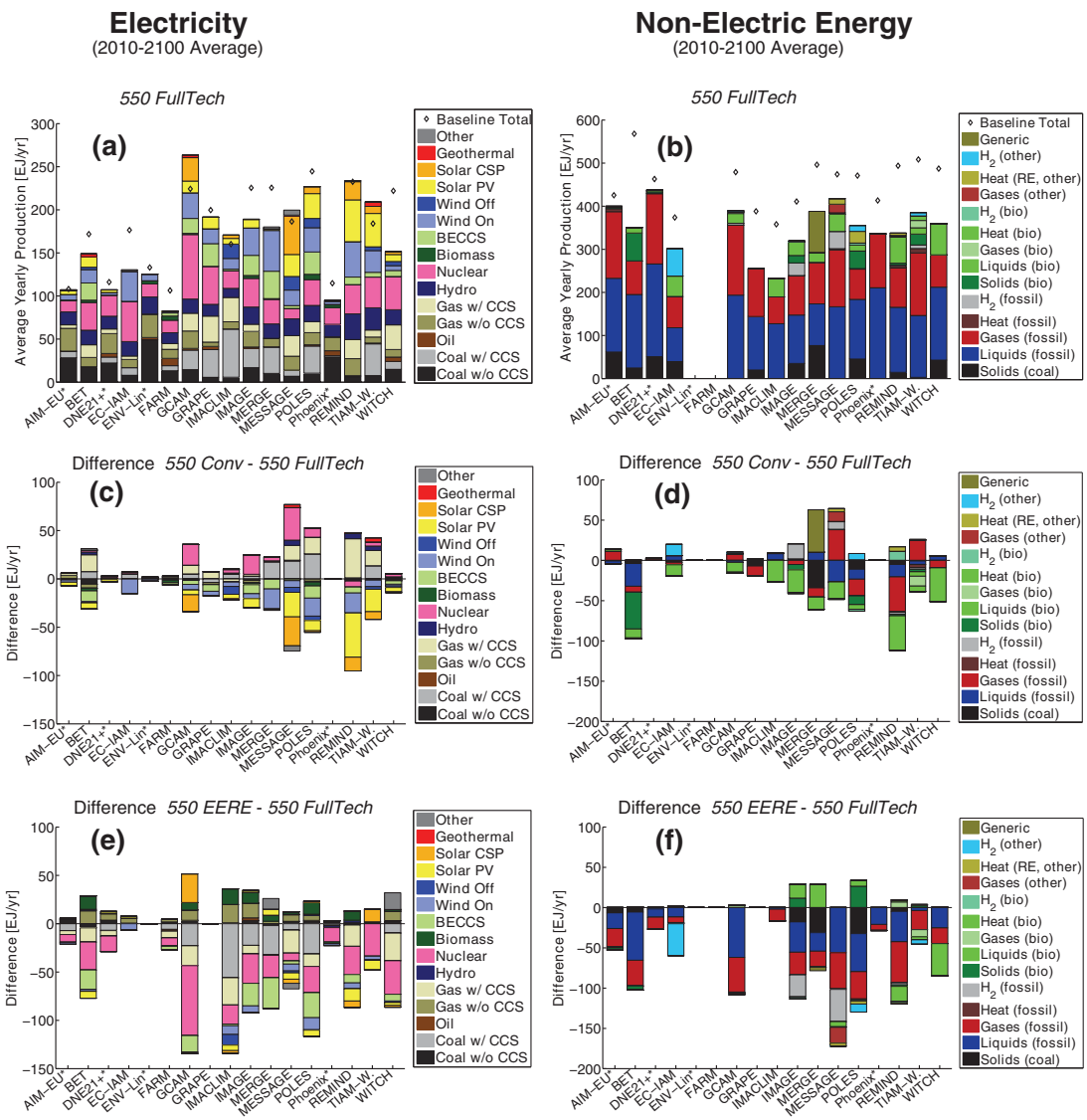


Fig. 2 Yearly electricity (*left column*) and non-electric secondary energy production (*right column*) averaged from 2010 to 2100 for the *550 FullTech* scenarios (**a**, **b**), as well as differences of *550 Conv* to *550 FullTech* (**c**, **d**) and *550 EERE* to *550 FullTech* (**e**, **f**). The *diamond markers* indicate totals in the *Base FullTech* scenarios. *For AIM-EU, DNE21+, and ENV-Linkages, we used the 2010–2050 time span

Given ample opportunities to produce electricity from non-biomass renewables, their overall climate mitigation potential depends critically on the scope of electrification of end use. A larger portion of end uses become electrified in low stabilization scenarios, cf. also Krey et al. (2013). In some models, electricity use under climate policy even exceeds baseline levels (cf. also Fig. 2a).

3.2 Substitution between RES and other low-carbon supply options

By exploring the technology variations in the EMF27 scenario set, we can determine if the large-scale deployment of wind, solar, and bioenergy power is critical for climate change mitigation (*Conv* scenario with limited RE availability), and if mitigation targets can be reached solely relying on energy efficiency and renewables (*EERE* scenario).

In the *FullTech* climate policy scenarios, the models agree on the strong decrease of fossil-based electricity without CCS, but show a variety of decarbonization pathways (Figs. 2a and 3a, b). For some models (REMIND, MESSAGE, POLES, TIAM-WORLD), nuclear and CCS are mostly relevant in the medium-term, while power supply is dominated by RES in the long-term. In other models (WITCH, EC-IAM, IMACLIM), nuclear, RES, and CCS contribute in roughly equal shares throughout the century. Electricity supply is very responsive to the technology variations in the EMF27 scenarios. CCS, nuclear, and renewables are alternative low-carbon options that represent good substitutes in carbon-constrained scenarios. The limitations on wind, solar, and bioenergy use imposed in the *Conv* scenario result in higher deployment of CCS and nuclear (Figs. 2c and 3b). Similarly, more wind, solar, and CCS technologies are used in the nuclear phase-out scenarios (NucOff; cf. Krey et al. 2013) while more wind, solar, and nuclear use results from the unavailability of CCS (NoCCS; cf. Fig. S3.1 and Krey et al. 2013).

Limited bioenergy availability has a considerable impact on non-electric energy supply in the *Conv* scenario (Fig. 2b, e). In most models, the supply of liquids, gases and solids decreases substantially compared to the *FullTech* scenario. There are two main reasons for this pattern. First, there is a lack of non-electric low-carbon substitutes for biofuels in most models.[2] Second, bioenergy has the potential to create negative emissions via combination with CCS (BECCS; see also Rose et al. 2013). Reducing bioenergy availability results in less negative emissions, resulting in less leeway for the continued use of fossil fuels for non-electric energy.

In the *EERE* scenario, the overall energy demand is lower than in the *FullTech* scenario (Fig. 2e, f). On the other hand, with CCS and nuclear unavailable, renewables are the only long-term low-carbon options for electricity supply. As a result, the share of RES in electricity supply is generally substantially higher in *EERE* than in *FullTech*, while deployment levels in absolute terms are similar. In many models, more coal and gas without CCS are used for electricity supply, resulting in a higher share of freely emitting sources than in *FullTech*. At the same time, the lack of the BECCS option to create negative emissions decreases the cumulative fossil use that is permissible within the climate constraint. This restriction results in additional reductions in fossil fuel use for non-electric energy in the *550 EERE* scenario. Biofuels increase only slightly in absolute terms, but their share is substantially higher than in the *FullTech* scenario.

3.3 The impact of RE availability on mitigation costs

The different roles that low-carbon energy technologies play in electric and non-electric energy are important factors for explaining the impact of technology constraints on the costs and feasibility of climate targets. Figure 4 displays the costs of reaching the 550 and 450 ppm climate policy targets under limited technology scenarios normalized to the costs in the corresponding *FullTech* scenarios. For the *Conv* scenarios, the EMF27 models show that limited availability of wind, solar, and bioenergy results in a substantial cost increase. This finding is in line with earlier studies, which found similar cost increases by examining climate policy scenarios with restrictions on the expansion of RE (Edenhofer et al. 2010; Pugh et al. 2011; Luderer et al. 2012). The EMF scenarios allow us to separate the effects of bioenergy availability (*LimBio* scenario) from limitations on wind and solar-power use (*LimSW* scenario). The models consistently find higher cost penalties for limiting biomass than for limiting solar and wind power in both the 550 and 450 ppm climate mitigation

[2] MERGE and EC-IAM are an important exception as they represent generic carbon-free backstop technologies for non-electric energy or hydrogen.

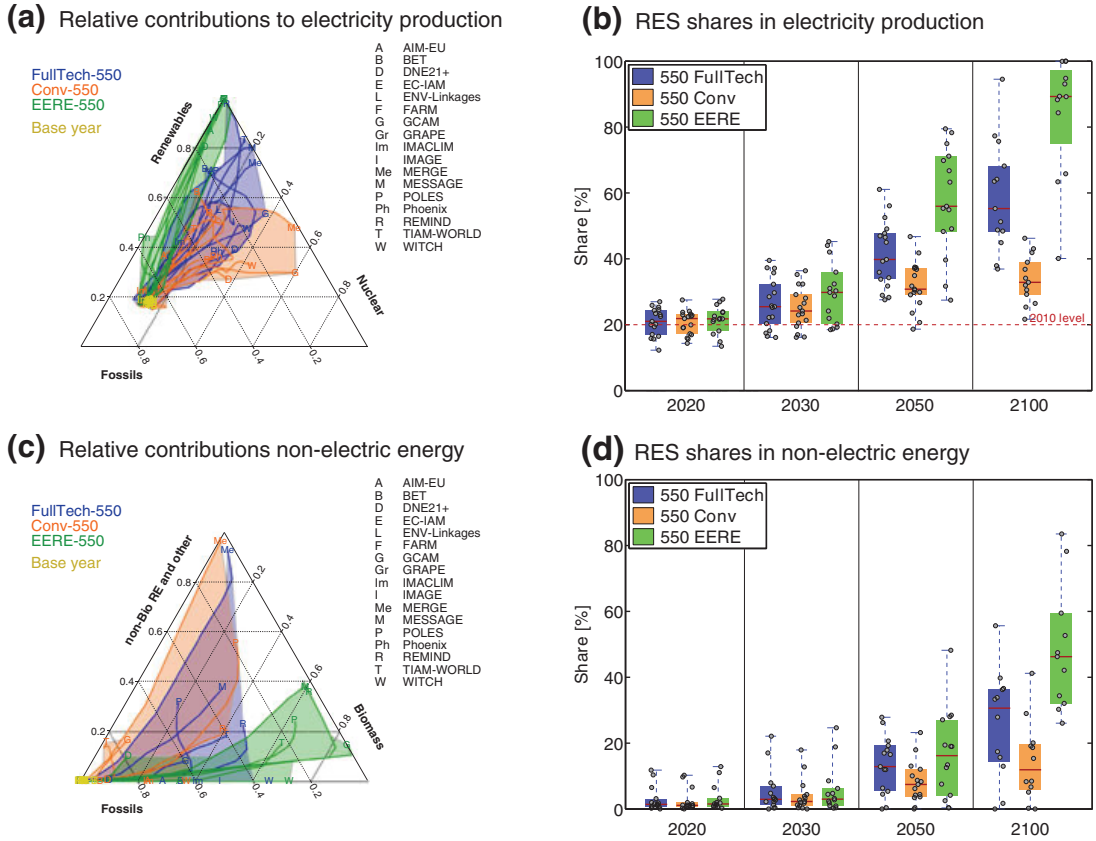


Fig. 3 Shares of RES in electric (**a**,**b**) and non-electric (**c**,**d**) secondary energy supply

scenarios. This is explained by the fact that in case of limitations on wind and solar power other low-carbon alternatives such as nuclear or CCS are readily available, while biomass is much harder to substitute (see discussion in Sections 2.4 and 3.2). The cost increases escalate if biomass, and wind and solar use are limited simultaneously (*Conv* scenarios).

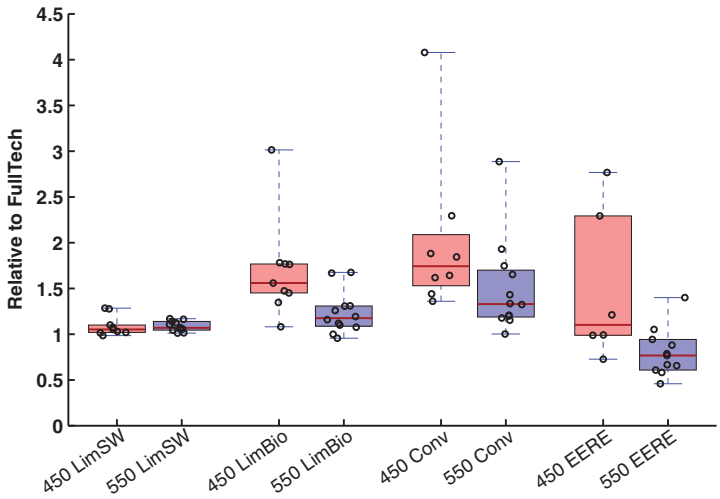


Fig. 4 Climate policy costs for scenarios with reduced technology portfolios, indexed relative to the corresponding *FullTech* scenario. See Kriegler et al. (2013) for a discussion of mitigation cost metrics

The *EERE* scenarios, which rely solely on energy efficiency and renewables for mitigation, offer a complementary perspective on the role of renewables for climate change mitigation. In terms of policy costs, two forces are at play. On the one hand, the lower baseline energy demand results in lower baseline emissions, and thus, a smaller mitigation gap towards the climate target. On the other hand, the unavailability of CCS and nuclear makes the mitigation effort more difficult than in the *FullTech* scenarios. This explains the wide range of policy cost outcomes. In the 550-ppm case, all models except DNE21+, MERGE, and POLES show lower costs in the *EERE* scenario than in *FullTech*. In the 450-ppm scenario, the split becomes more extreme: almost half the models found the 450 ppm target infeasible in the *EERE* setting, while in most of the other models (such as WITCH and Phoenix), policy costs in the *EERE* scenario are lower than in *FullTech.*

4 Determinants of wind and solar power deployment

As noted in Section 2, the observed deployment levels of different renewable energy sources differ strongly across the models participating in EMF27. The objective of this section is to relate RE deployment levels to model assumptions and characteristics. We discuss three key determinants of deployment levels: direct economic costs, resource availability, and systems-integration constraints. While they provide valuable insights, none of these factors taken by themselves can explain the range of RE deployment results across the various models. This indicates that the relative importance of these determinants depends on model-specific assumptions and region-specific circumstances. Detailed information and data about RE parameters and assumptions are available for the seven models that participated in the EMF27 RE subgroup (DNE21+, GCAM, IMAGE, MERGE, MESSAGE, POLES and REMIND). The diagnostic analysis in this section focuses on these models and the USA and China model regions.

4.1 Technology costs and competition with other technologies

Technology choices in energy-economic models are typically the result of a cost minimizing or welfare maximizing optimization procedure, or an explicit selection based on levelized costs. Electricity generation costs of RES vis-à-vis nuclear and CCS therefore have a crucial influence on the economic deployment potential in the context of climate change mitigation. However, not only direct technology costs but also indirect factors, such as integration costs, resource potentials and other constraints represented in the models affect deployment levels.

Since no fuel costs are incurred for wind and solar power, their levelized costs of electricity generation (LCOEs) at a given location are largely driven by capital cost. Most models project capital costs in the range of 800−1,400 $/kW for solar PV and 750−1,000 $/kW for wind onshore in 2050 (Table S2.1). For IMAGE, capital costs for onshore wind turbines are considerably lower than in the other models, while MERGE has substantially higher costs for solar power. REMIND, IMAGE, and POLES treat technological learning endogenously, resulting in lower capital costs in the policy scenarios compared to the baseline. Figure 5 contrasts LCOE and deployment levels for solar, wind, nuclear, gas CCS, and coal CCS in the USA and China averaged over all installations in 2050 for the *450 FullTech* scenario. Deployment levels within one model roughly mirror LCOE patterns in the sense that technologies with lower LCOEs tend to be deployed at higher levels. However, average direct LCOEs are an imperfect indicator of technology use, as in several cases the order of technology deployment is not in line with relative costs. This is because

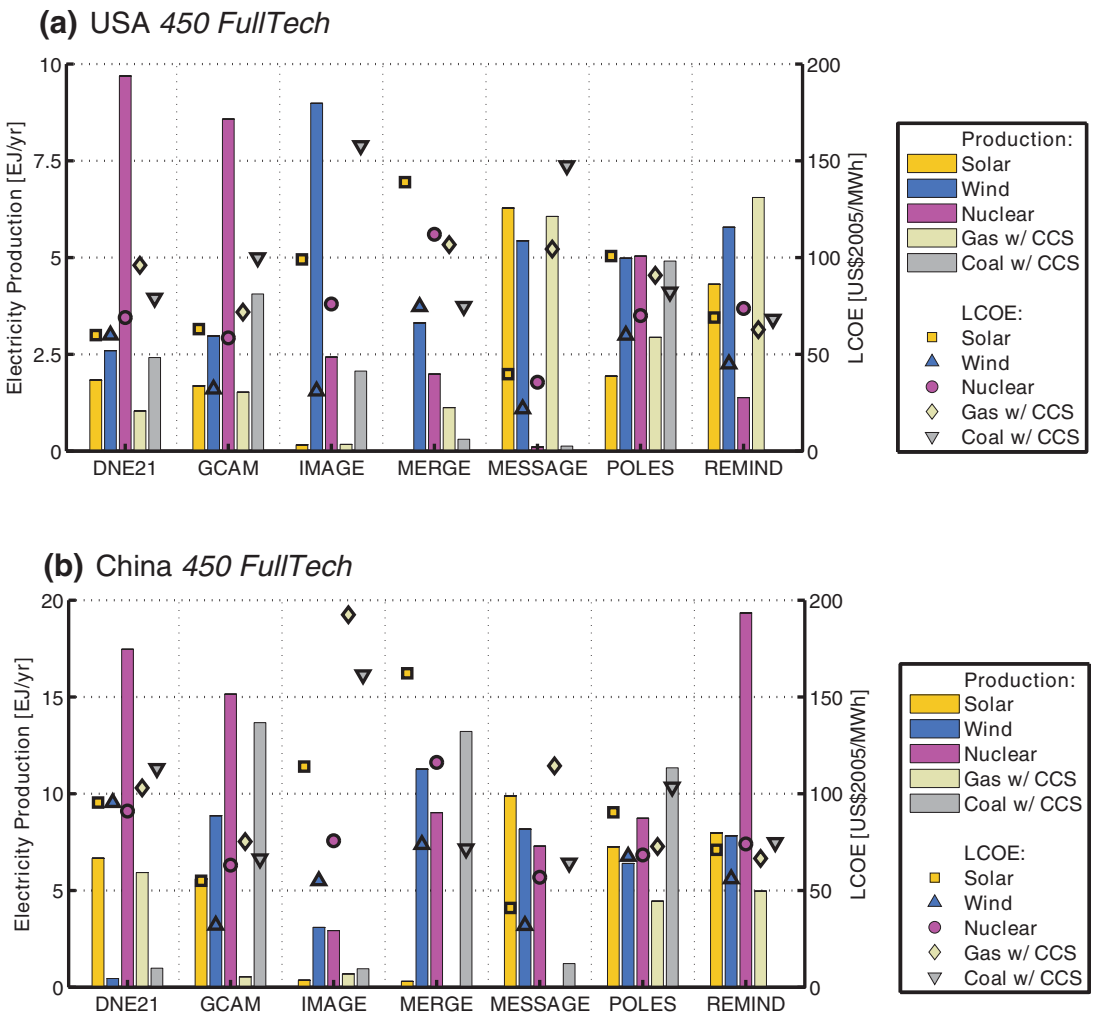


Fig. 5 Deployment levels of selected low-carbon technologies (*bars*, *left axis*) and corresponding average direct LCOE (*markers*, *right axis*) for the *450-FullTech* Scenario in 2050. *Upper row*: USA; *lower row*: China

direct LCOEs only account for capital costs, O&M costs, fuel costs and residual CO_2 emissions, but do not reflect other economic or physical constraints implemented in the models, such as integration costs, risk premiums or constraints on waste or CO_2 storage capacities in the case of nuclear and CCS. In addition, the LCOEs are calculated for one point in time and do not account for intertemporal effects, such as the inertia in capital turnover, or the anticipation of learning-by-doing.

By 2050, models project direct costs of wind power to be comparable or even lower than electricity production from nuclear or fossil CCS plants. For all the models except DNE21+ and MESSAGE, onshore wind power deployment is considerable in the USA and China. Solar energy tends to be more expensive than wind power. In some of the models, limitations on resource size and quality limitations are a constraint for wind deployment in China, which explains the comparatively low onshore wind deployment levels in DNE21+, IMAGE and MESSAGE (see Section 4.2).

Due to high cost assumptions, solar power is not deployed in MERGE, and remains insignificant in IMAGE. Solar power is more important in the other models, which all see more than 5 EJ/year of electricity produced from solar technologies in China. In REMIND, which operates under perfect foresight, the anticipation of benefits from technological

learning results in an earlier and higher deployment of solar PV, despite temporarily higher LCOEs.

4.2 Renewable energy resource potentials

Another key determinant for RE deployment in model scenarios and in the real world is the quantity and quality of the resource. Resource quality has direct implications for economic costs (Section 4.1).

Figure 6 shows the onshore wind and solar PV technical resource potentials assumed by the selected models in the USA and China next to the respective deployment pathways in the *450 FullTech* scenario. This comparison reveals that assumptions about technical resource potentials at the regional level differ vastly across models. In both regions, the lowest and highest resource potential estimates differ by more than one order of magnitude across the models and in some cases, turn out to be binding for the observed deployment levels. In addition, resource quality—characterized by the capacity factors (see bar charts in Fig. 6 and Figs. S4.1−S4.3)—varies across the data sets by a factor of two in the best resource categories represented in the models. When comparing deployment levels with resource potentials at the regional level, the renewable resource data adopted by the different IAMs can explain some of the differences in the deployment of onshore wind turbines. For example, the upper end of the regional supply curve determines the maximum deployment in at least one model (MERGE), but others are close to the maximum deployment level as well (e.g. IMAGE in China). A similar comparison for solar PV shows that the resource potentials included in the models tend to be significantly higher than for wind (with the

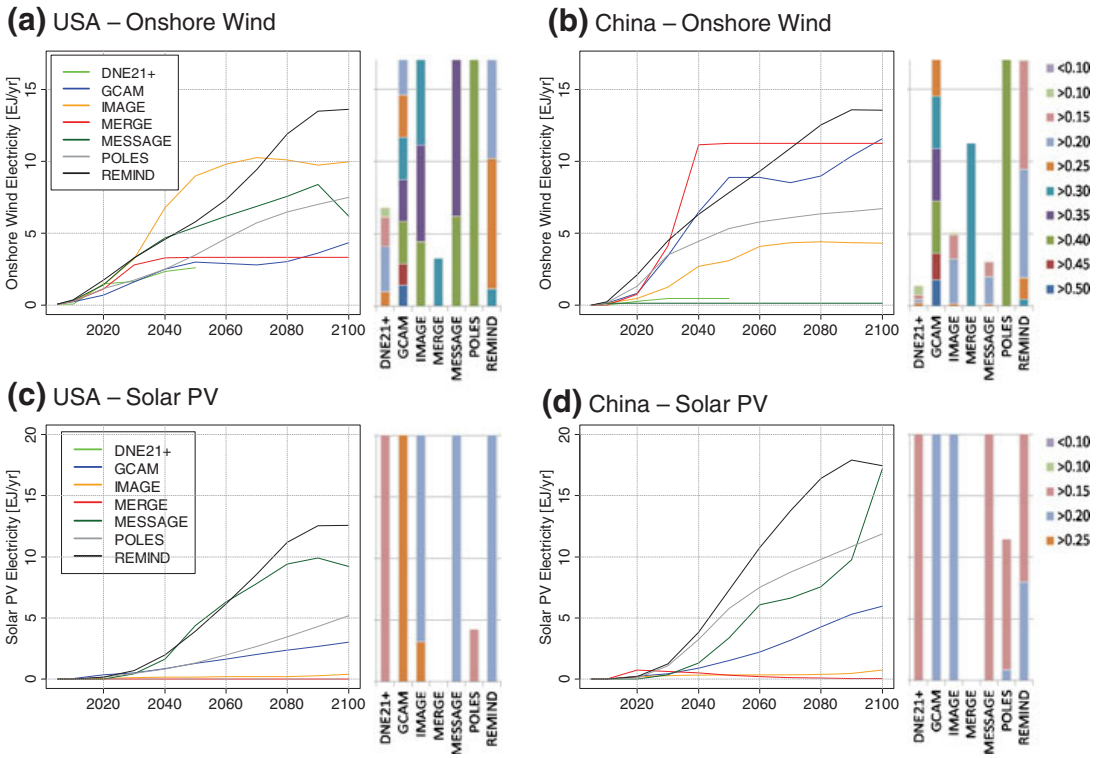


Fig. 6 Onshore wind and solar PV deployment (*lines*) and resource potentials by capacity factor (*bars*) in the USA (*left*) and China (*right*) for the *450 FullTech* scenario. Note that regional definitions are not fully comparable in all cases and that for some models, offshore wind data are combined with onshore wind (see SM)

exception of POLES, where only rooftop PV is considered). Therefore, total resource availability typically is not a limiting factor for PV technology deployment. Instead, cost assumptions as well as competition with other technologies are much more relevant (Section 4.1).

In part, the differences in resource potentials are due to definitional issues, which make them difficult to compare. However, it is possible to trace many of these differences back to the original resource data sets employed by the models, which in turn, are based on different methodologies and show a considerable spread.

4.3 Systems integration of variable renewable energies (VRE)

One crucial drawback of wind and solar power is the spatial heterogeneity and temporal variability of their outputs. Many of the EMF27 scenarios describe electricity systems with a high penetration of variable renewable generation in excess of 30 %. The need to match load and supply at all times in such systems can require major changes to the operation and design of current electricity systems. RE fluctuations occur on time scales that are much smaller than the annual to decadal time-scales typically resolved by IAMs focusing on the long-term transformations dynamics. Therefore, these models represent RE integration challenges in a rather stylized way. Table S4.3 provides an overview of the systems-integration mechanisms represented in the models. The most basic approach to reflecting integration challenges is to set an exogenous constraint on the maximum share of wind and solar power in electricity generation. For instance, BET limits the combined share of wind and solar to 30 %. Similar constraints are implemented in AIM-Enduse, BET, EC-IAM, FARM, GRAPE, IMACLIM and POLES. These models tend to have relatively low overall RE shares in the electricity supply. Over the last years, experience with integrating VRE into power systems has increased (for instance, shares of wind and solar in total 2012 electricity generation were greater than 27 % in Denmark), and first detailed power system studies have explored scenarios with VRE shares of 30 %, 40 % and higher (NREL 2010; Mills and Wiser 2012; NREL 2012). These developments suggest that hard bounds may substantially overestimate integration challenges.

Other approaches make the economic trade-offs related to RE integration more explicit by introducing storage and backup requirements or cost penalties increasing with RE penetration, or by representing load duration curves. Many models use a combination of several approaches. The system-integration costs mapped by these approaches can be substantial. For instance, they amount to ~23 $/MWh at 20 % PV and 15 % wind penetration for REMIND in the *450 FullTech* scenario in the USA in 2050. Similarly, a cost penalty on wind deployment amounting to 15 $/MWh is applied in MERGE, while in GCAM integration costs are as high as 37$/MWh at 10–15 % wind share. The lower end of this range is roughly consistent with the results obtained by detailed studies on integration costs (Mills and Wiser 2012; Ueckerdt et al. 2013; Hirth 2013).

Including integration challenges more explicitly in the models does not necessarily lead to lower VRE deployment: In several of the models considering integration challenges explicitly, wind and solar power combined account for more than 40 % of electricity supply in the latter half of the 21st century (MESSAGE, REMIND and TIAM-WORLD) . On the other hand, integration challenges are crucial in explaining relatively low solar PV deployment levels in other models (GCAM and IMAGE). Future research is needed to validate the implicit and explicit integration costs represented in IAMs with detailed bottom-up studies spanning a larger scenario space with various combinations of VRE shares and flexibility options, as well as covering various regions.

5 Conclusions

This paper analyzes the role of RES in climate change mitigation based on a large set of state-of-the-art IAMs and the coordinated scenario set provided by the EMF27 study.

One important conclusion is that the relevance of RES is very different in the various energy supply sectors. Renewables can play an important or even dominant role in the power sector. In most models, the use of RES for electricity increases even without climate policies. In mitigation scenarios, RE deployment for electricity supply expands considerably, with an increasing share of wind power in all models and substantial long-term deployment of solar power in most models.

Another important insight from the EMF-study is that the decarbonization of fuels for transport, buildings and industry are crucial bottlenecks for reducing energy related emissions. Bioenergy is a versatile substitute for fossil fuels that can produce various energy carriers, and therefore is by far the most important mitigation option for non-electric energy production. The EMF27 scenarios suggest that renewable power in combination with electrification of end-use (e.g. via electric vehicles, electric arc furnaces, or geothermal heat pumps) is an important mitigation option. Beyond electrification, renewables can contribute via low-temperature heat. Solar-thermal energy systems account for a substantial share of heat supply in the few models in which they are represented. Given the potential importance of renewable heat supply, a broader and more refined representation in IAMs as well as efforts to improve bottom-up estimates of their deployment potential seem desirable.

Restricting the penetration of wind and solar energy to 20 % of electricity supply has a relatively small effect on the costs of climate policy, if nuclear and CCS are available. This is not a surprise since wind, solar, nuclear and CCS are substitutes for low-carbon electricity. In contrast, limiting the availability of bioenergy to 100 EJ/year results in significantly higher cost increases not only because of its importance for decarbonizing non-electric energy supply, but also the possibility of generating negative emissions by combining bioenergy production with CCS. Most EMF27 models also find it difficult or even impossible to reach the 450 ppm climate target by relying on energy efficiency and renewable energy alone, i.e., without CCS and nuclear energy.

While many of the findings regarding the potential role of RES for climate mitigation are rather robust, the deployment levels of individual technologies vary considerably across models. An in-depth analysis based on a subset of EMF27 models shows that the diversity of the results mirrors the wide range of assumptions on crucial parameters. In particular, there is a substantial discrepancy between the RE resource assumptions used in the models. Therefore, it is necessary to derive new global resource data sets for the most frequently discussed options (e.g., wind, solar PV, CSP) as well as for the less well-represented options (e.g., solar heat, geothermal heat). Moreover, there is substantial uncertainty about the future evolution of technology costs for RES and relevant competing low-carbon technologies. In the past, renewable technologies have shown considerable cost reduction potential. Improved estimates of future costs and an explicit treatment of related uncertainties will be important to improve further our understanding of the role of RES. Finally, spatial heterogeneity and temporal variability is an important characteristic of wind and solar energies. The EMF27 models represent the implications of variable RES in a variety of stylized ways, which can have potentially crucial effects on the results. Further research is necessary to develop improved, yet tractable methodologies.

Acknowledgements The contribution of GL, VK, RP and JVV to this research was supported by funding from the European Commission's Seventh Framework Programme under the LIMITS project (grant agreement no. 282846).

References

Arvizu D, Balaya P, Cabeza LF, Hollands KGT, Jäger-Waldau A, Kondo M, Konseibo C, Meleshko V, Stein W, Tamaura Y, Xu H, Zilles R (2011) Direct solar energy. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, von Stechow C (eds) IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press, Cambridge

Chum H, Faaij A, Moreira J, Berndes G, Dhamija P, Dong H, Gabrielle B, Eng AG, Lucht W, Mapako M, Cerutti OM, McIntyre T, Minowa T, Pingoud K (2011) Bioenergy. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, von Stechow C (eds) IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press, Cambridge

Edenhofer O, Knopf B, Barker T, Baumstark L, Bellevrat E, Chateau B, Criqui P, Isaac M, Kitous A, Kypreos S (2010) The economics of low stabilization: model comparison of mitigation strategies and costs. Energy J 31:11–48

Hirth L (2013) The market value of variable renewables: the effect of solar wind power variability on their relative price. Energy Econ 38:218–236. doi:10.1016/j.eneco.2013.02.004

IEA (2012) Energy Balances of non-OECD Countries - 2012 edition. International Energy Agency, Paris

IPCC (2011) Special report renewable energy sources and climate change mitigation. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, Stechow CV (eds) Intergovernmental Panel on Climate Change

Krey V, Clarke L (2011) Role of renewable energy in climate mitigation: a synthesis of recent scenarios. Clim Pol. doi:10.1080/14693062.2011.579308

Krey V, Luderer G, Clarke L, Kriegler E (2013) Getting from here to there – energy technology transformation pathways in the EMF-27 scenarios. Clim Chang. doi:10.1007/s10584-013-0947-5

Kriegler E, Weyant JP, Blanford GJ, Krey V, Clarke L, Edmonds J, Fawcett A, Luderer G, Riahi K, Richels R, Rose SK, Tavoni M, van Vuuren DP (2013) The role of technology for achieving climate policy objectives: Overview of the EMF 27 study on global technology and climate policy strategies. Clim Chang. doi:10.1007/s10584-013-0953-7

Kumar A, Schei T, Ahenkorah A, Rodriguez RC, Devernay J-M, Freitas M, Hall D, Killingtveit Å, Liu Z (2011) Hydropower. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, von Stechow C (eds) IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press, Cambridge

Luderer G, Bosetti V, Jakob M et al (2012) The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison. Clim Chang 114:9–37. doi:10.1007/s10584-011-0105-x

Mills A, Wiser R (2012) Changes in the Economic Value of Variable Generation at High Penetration Levels: A Pilot Case Study of California. http://emp.lbl.gov/sites/all/files/lbnl-5445e.pdf

NREL (2010) Western wind and solar integration study. National Renewable Energy Laboratory (NREL), Golden, CO. http://www.osti.gov/energycitations/product.biblio.jsp?osti_id=981991

NREL (2012) Renewable Electricity Futures Study. Hand, M.M. et al. NREL/TP-6A20-52409. National Renewable Energy Laboratory, Golden, CO.

Pugh G, Clarke L, Marlay R, Kyle P, Wise M, McJeon H, Chan G (2011) Energy R&D portfolio analysis based on climate change mitigation. Energy Econ 33:634–643. doi:10.1016/j.eneco.2010.11.007

Rogner H-H, Aguilera RF, Bertani R et al (2012) Chapter 7 - Energy resources and potentials. In: Global energy assessment - toward a sustainable future. Cambridge University Press, Cambridge, pp 423–512

Rose SK, Kriegler E, Bibas R, Calvin K, Popp A, van Vuuren D, Weyant J (2013) Bioenergy in energy transformation and climate management. Clim Chang. doi:10.1007/s10584-013-0965-3

Sathaye J, Lucon O, Rahman A, Christensen J, Denton F, Fujino J, Heath G, Mirza M, Rudnick H, Schlaepfer A, Shmakin A (2011) Renewable energy in the context of sustainable development. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, von Stechow C (eds) IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press, Cambridge

Turkenburg WC, Arent DJ, Bertani R, Faaij A, Hand M, Krewitt W, Larson ED, Lund J, Mehos M, Merrigan T, Mitchell C, Moreira JR, Sinke W, Sonntag-O'Brien V, Thresher B, van Sark W, Usher E, Usher E (2012) Chapter 11 - Renewable energy. In: Global energy assessment - toward a sustainable future. Cambridge University Press, Cambridge, pp 761–900

Ueckerdt F, Hirth L, Luderer G, Edenhofer O (2013) System LCOE: What are the Costs of Variable Renewables? Social Science Research Network, Rochester, NY. http://papers.ssrn.com/abstract=2200572

Wiser R, Yang Z, Hand M, Hohmeyer O, Infield D, Jensen PH, Nikolaev V, O'Malley M, Sinden G, Zervos A (2011) Wind energy. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, Zwickel T, Eickemeier P, Hansen G, Schlömer S, von Stechow C (eds) IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press, Cambridge

The role of renewable energy in climate stabilization: results from the EMF 27 scenarios – supplementary material

2 RE deployment levels

This section provides about the representation of specific RE technologies in models, and additional information about deployment levels.

2.1 Technology representation in EMF27 models

	Electricity												Hydrogen				Liquids		Heat				Transp.	
Model	Bioenergy w/o CCS	Bioenergy w/ CCS	Geothermal Power	Solar Power (generic)	Solar Power|Central PV	Solar Power|Distributed PV	Solar Power|CSP	Wind Power (generic)	Wind Power|Onshore	Wind Power|Offshore	Hydroelectric Power	Ocean Power	Biomass to Hydrogen w/o CCS	Biomass to Hydrogen w/ CCS	Solar Thermochemical Hydrogen	Electrolysis	Biomass to Gas w/o CCS	Biomass to Gas w/ CCS	Biomass Heat	Geothermal Heat	Solarthermal Heat	CHP (coupled heat and power)	Electric Vehicles	Hydrogen Vehicles
AIM-Enduse	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
BET	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
DNE21+	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
EC-IAM	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
ENV-Linkages	■	■	**	*	■	■	■	*	■	■	**	■	■	■	■	■	■	■	■	■	■	■	■	■
FARM	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
GCAM	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
GCAM-IIM	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
GRAPE	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
IMACLIM	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
IMAGE	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
MERGE	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
MESSAGE	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Phoenix	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
POLES	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
REMIND	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
TIAM-WORLD	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
WITCH	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Sum	18	15	10	17	9	5	9	18	8	6	18	1	9	8	3	9	8	4	5	2	3	7	16	11

Table S2.1: Overview of RE technology coverage in different sectors across the models participating in EMF27. * In ENV-Linkages, wind and solar are aggregated into one variable renewable energy supply technology. ** In ENV Linkages, hydroelectric and geothermal power are aggregated into one generic base-load renewable energy supply technology.

2.2 The role of different renewable energy sources in the EMF27 scenarios

This section provides additional information on the development RE deployment levels, supplementing the material presented in Sections 2.1-2.5 of the main paper.

2.2.1 Geothermal electricity

Conventional electricity generation from hydrothermal reservoirs is already mature, but at present, it plays a minor role in current energy systems, accounting for approximately 0.2% of global electricity generation in 2010 (IEA 2012). The resource potentials for hydrothermal electricity generation are limited: Goldstein et al. (2011) report a range of 28–56 EJ/yr. Enhanced geothermal systems (EGS) have a considerably larger resource potential (89–1052 EJ/yr as reported by Goldstein et al. (2011), but the technology is less mature. Many of the EMF27 models do not consider geothermal power, and others only represent it in a rather stylized way (e.g., REMIND). TIAM, BETS, AIM/CGE, and GCAM are the most optimistic about geothermal power, but feature deployment levels of 7 EJ/yr or lower (Figure S2.1).

2.2.2 Non-biomass RES for heat supply

In addition to biomass, geothermal and solar sources can provide renewable heat supply. In 2010, the installed capacity for solar heat production was an order of magnitude larger than the capacity for solar electricity production (Arvizu et al. 2011). Deployment is substantial in climate policy cases in the few models that represent these options (Figure S2.1). For *450 FullTech,* solar heating systems account for 16-34 EJ/yr in 2050 in POLES and MESSAGE, a substantial share of total heat supply. For the same scenario, geothermal heat supply is 0.4 EJ in MESSAGE and 5.1 EJ in REMIND.

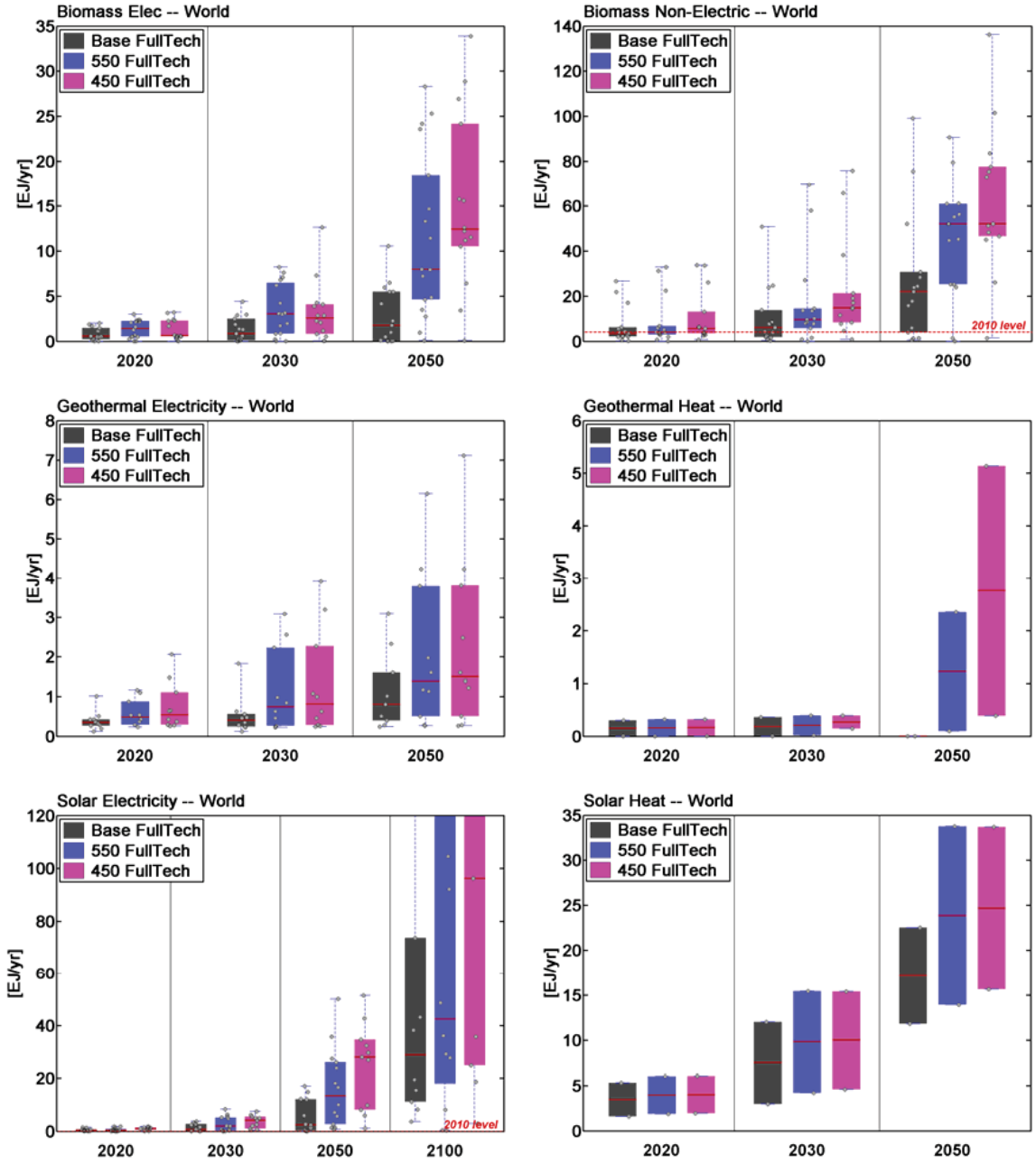


Figure S2.1: Energy supply from various RE technology groups in the Base, 550 and 450 FullTech scenarios. Boxes represent 25th-75th percentiles, the red line the median, whiskers the full range of results.

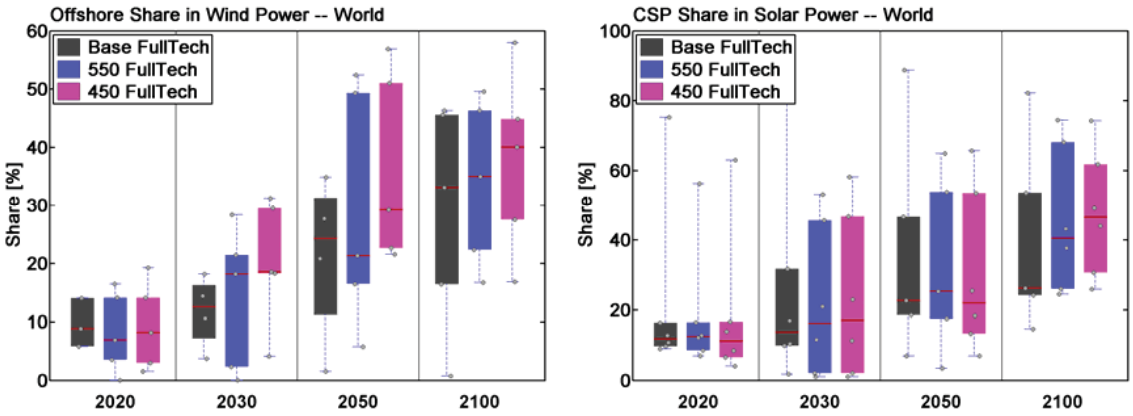


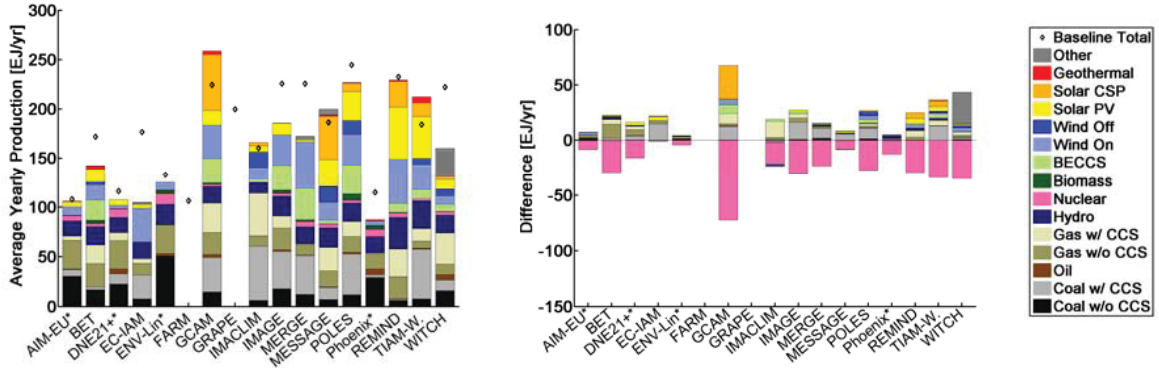
Figure S2.2: Share of offshore in wind electricity supply, and CSP in solar electricity supply.

s

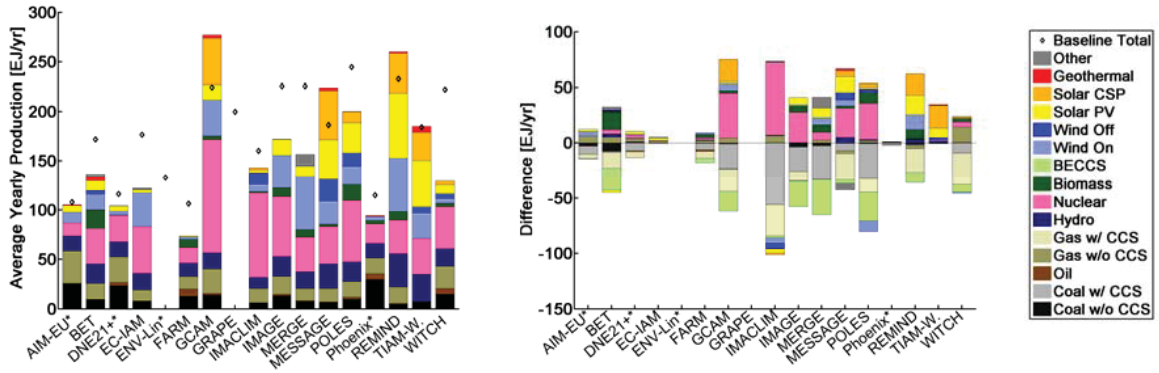
3 The relevance of RE for mitigation

This section provides additional information on marginal substitutions in technology-constraint scenarios.

(a) Electricity (2010-2100) – 550 NucOff (b) Difference 550 NucOff – 550 FullTech



(c) Electricity (2010-2100) – 550 CCSOff (d) Difference 550 CCSOff – 550 FullTech



(e) Electricity (2010-2100) – 550 LimSW (f) Difference 550 LimSW – 550 FullTech

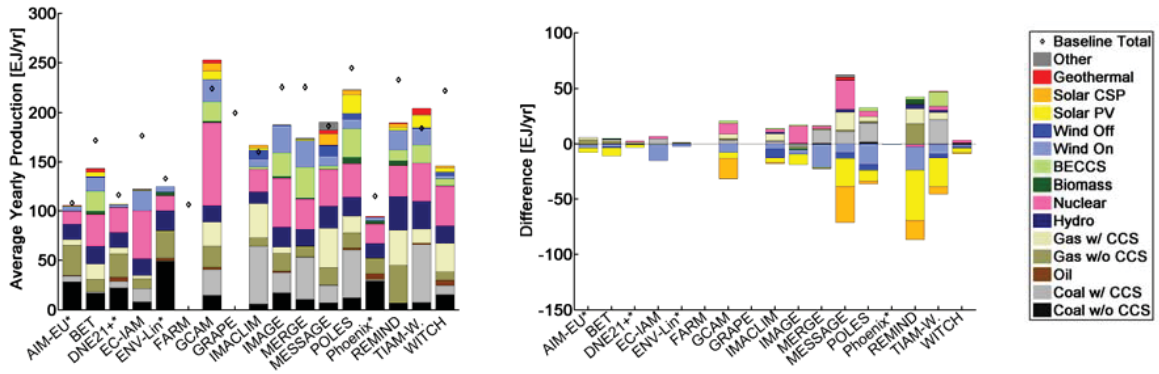


Figure S3.1: Average yearly electricity production from 2010-2100 for the 550 ppm climate stabilization scenarios with technology limitations: (a) NucOff (nuclear phase out), (c) CCSOff (CCS assumed to be unavailable), and (e) LimSW (solar and wind power limited to 20% of electricity generation). Difference in deployment between relative to the 550 AllTech scenario are shown in (b), (d) and (f). * For AIM-EU, DNE21+ and ENV-Lin, the time span 2010-2050 was considered. Diamonds markers indicate totals in the Base AllTech scenarios. **For Phoenix, the time span 2010-2070 was considered

4 Determinants of wind and solar power deployment

This section provides additional information on wind and solar resource potentials in the eight energy-economic and integrated assessment models that were part of the renewable energy subgroup of the EMF27 modeling intercomparison exercise.

4.2 Technology costs and competition with other technologies

	2050 capital costs $2005/kW				
	PV	CSP	wind on	wind off	learning?
DNE21	850		900		Exogenous
GCAM	750	1900	750		Exogenous
IMAGE	1000-1100		350-400		Endogenous
MESSAGE	1250	1600	870	1300	Exogenous
POLES	1200-1400	1500-1600	1000	1850	Endogenous (relatively small cost decreases)
REMIND	1000-2100	5200-8300	990-1030		Endogenous

Table S4.1: Assumptions on capital costs for different models.

Note that different power technologies experience different financing costs, either due to different build times (PV plants take 0.5-1 year to construct, nuclear plants usually take 4-10 years) or different interest rates. These financing costs can result in markups on investment costs of up to 20%. All of the models reflect these financing costs in one way or another and include this effect in the LCOE calculation.

4.3 Renewable energy resource potentials

The following two Figures S4.1 and S4.2 show the full onshore wind and solar PV resource supply curves in eight selected models.

(a) USA

(b) China

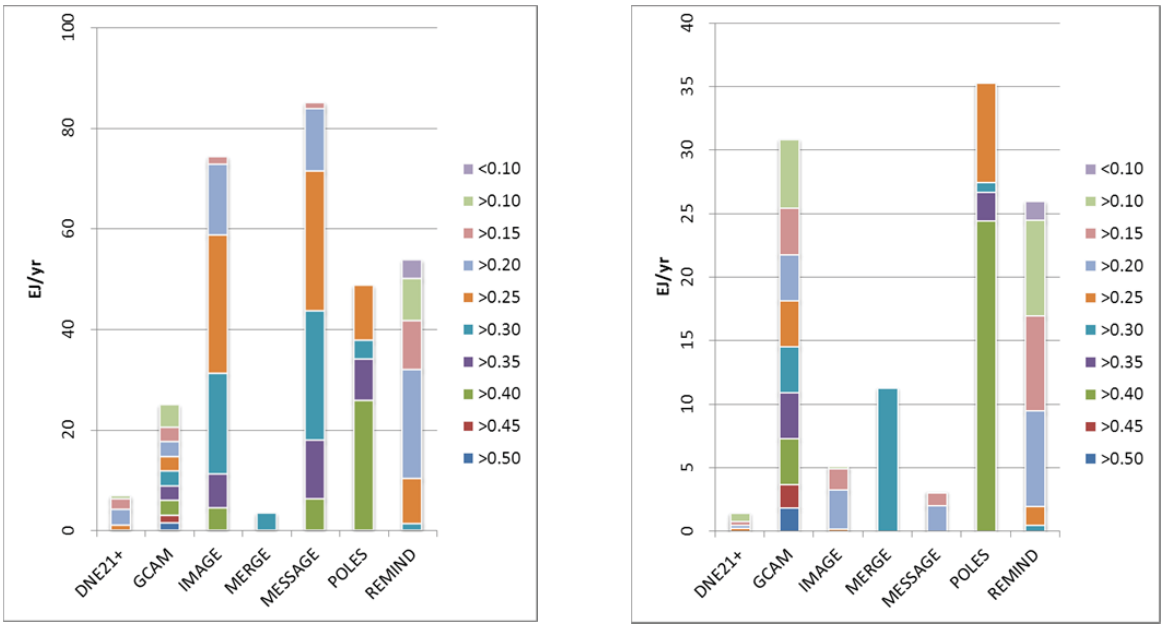


Figure S4.1: Full onshore wind resource potentials by capacity factor in the USA (a) and China (b) in selected models participating in the EMF27 study. Note that regional definitions are not exactly comparable in all cases (SM, Section 4.2.1) and that differences in the definition of resource potentials also exist (SM, Section 4.1.2).

(a) USA

(b) China

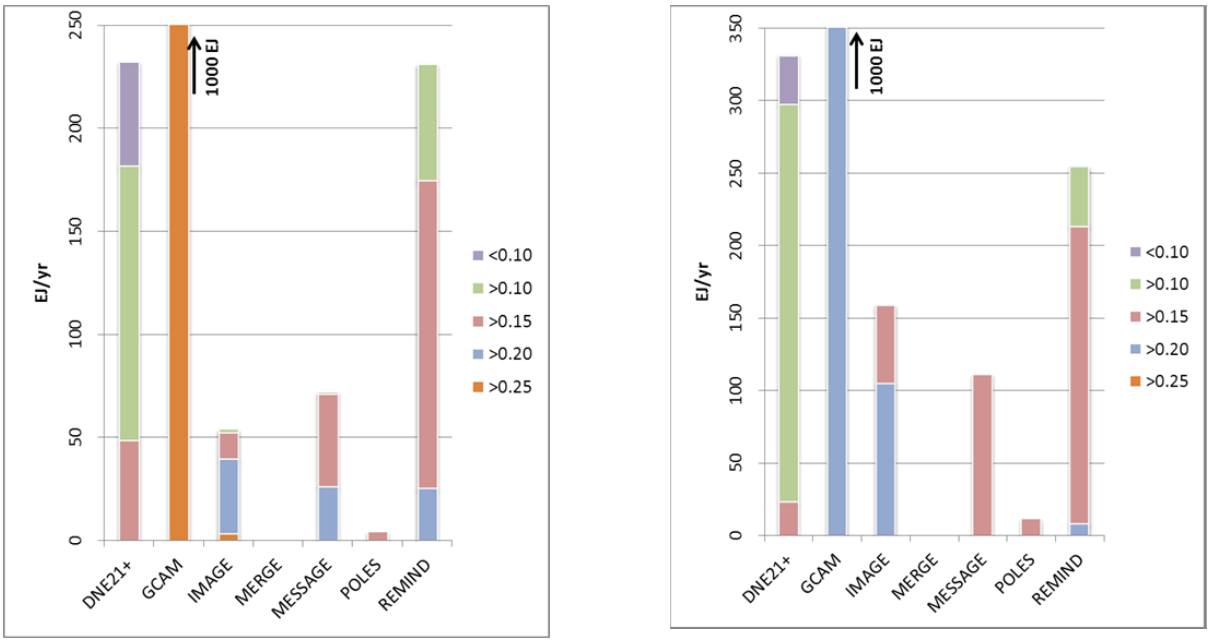


Figure S4.2: Solar PV resource potentials by capacity factor in the USA (a) and China (b) in selected models participating in the EMF27 study. Note that regional definitions are not exactly comparable in all cases (SM, Section 4.2.1) and that differences in the definition of resource potentials also exist (SM, Section 4.2.2).

4.3.1 Resource potential definitions

In part the differences in resource potentials are due to definitional issues which make a strict comparison of the potentials among model challenging (see SM, Section 4.1.2). However, a good chunk of the differences can be traced back to the original resource data sets employed by the various models which also show a considerable spread (Table S4.1). Reasons for the difference across the resource data sets relate to a number of factors, such as the resolution of the raw resource data sets where lower spatial resolution tends to average out high quality potential (in particular in the case of wind), but also to the choice of exclusion zones that define areas that cannot be used for exploiting the technical resource potential for various reasons that depend on the resource type (e.g., protected habitats, human settlements, conflicts with other infrastructure). In addition, global data sets which are adopted by the energy-economic and integrated assessment modeling community in some cases are significantly different from national or regional assessment. For example, the wind supply curve for China constructed by McElroy et al. (2009) extends to about 35 PWh (126 EJ) at bus bar costs of less than 0.8 RMB/kWh (corresponding to about 13 US-ct/kWh at current market exchange rates of 0.16025 USD/RMB).[1]

	Onshore wind	Solar PV
DNE21+	Own estimate based on National Climatic Data Center (NCDC-NOAA) data	Own estimate based on National Aeronautics and Space Administration (NASA) data
GCAM	Kyle et al. (2007)	
IMAGE	Hoogwijk (2004)	Hoogwijk (2004)
MESSAGE	Hoogwijk (2004)	Hoogwijk (2004)
POLES	Held (2010)	Held (2010)
REMIND	Own data set based on Hoogwijk (2004), Hoogwijk and Graus (2008), EEA (2009)	Own data set based on Tzscheutschler (2005). Trieb et al. (2009), DLR (direct communication)

Table S4.2: Literature sources on which the onshore wind and solar PV resource supply curves in the eight selected models are based.

The wind resource potentials listed for REMIND in contrast to the other models include offshore wind. As discussed in Section 2.1 of the main text, MESSAGE and POLES also include offshore wind resource potentials, but these are separately represented and not included in the data shown in this paper.

In the GCAM model, distance to the transmission grid is included in the wind resource supply curves. To make the data comparable to that shown for the other models, what is shown here are effective capacity factors that include a penalty for costs of constructing transmission lines.

Given the large technical potential for solar PV compared to current as well as future energy demand, GCAM does not have a finite limitation of the solar PV resource supply curve. As in the real world, the

[1]It should be noted that top-down methodologies for estimating wind energy potentials globally based on energy conservation estimate much lower potentials than bottom-up studies as the ones quoted above (De Castro et al. 2011).

deployment is constrained by system integration constraints rather than by limitations on the physical resource basis. In case of the POLES model the solar PV resource potential is limited to rooftop installations.

For the POLES model, the resource potential for both onshore wind and solar varies over time and the values shown here reflect the situation in 2050 which explains why for solar PV both in the USA and China the deployment of solar PV exceeds the potential slightly (cf. Figure S4.1).

These results illustrate that the availability of good renewable resource data sets is an important ingredient for reproducible and more comparable modeling of renewable energy deployment. An effort to derive new global renewable resource data sets for the options that are most frequently discussed (e.g., wind, solar PV, CSP), but also for less well represented options (e.g., geothermal heat, ocean energy) is therefore needed. Ideally such assessments would – to the degree possible – take into account findings from available national and regional studies to improve the representation of renewable energy technologies in IAMs. Moreover, given the number of uncertain factors (technical and non-technical), such an effort should not result in a single dataset that would surely improve comparability across models, but at the same time may lead to overconfidence of results if uncertainties are not reflected. High quality data sets that cover the main uncertainties for resource availability are needed.

4.3.2 Region definitions

The eight models for which we compare deployment levels of wind and solar PV in detail exhibit some differences in regional definitions which in part are responsible for the differences in resource potentials.

In contrast to the other models, MESSAGE combines Canada with the USA in a joint North America region, data for which is shown in the respective USA figures.

For China, several models include regions and countries other than China mainland.

- GCAM includes China, Mongolia, Cambodia, DPR Korea and Viet Nam
- IMAGE includes China, Mongolia, Taiwan, Hong Kong and Macao
- MESSAGE includes China, Cambodia, China, Hong Kong, Macao, DPR Korea, DPR Laos, Mongolia, Viet Nam

4.4 Systems Integration

	Cost Penalty	Storage	Backup Capacity	Load Duration Curve	Maximum share	Integration costs @20% share, $/MWh	No Mechanism
AIM-Enduse		Y			50% (solar+wind)		
BET			Y	Y	30% (solar + wind)		
DNE21+		Y	Y	Y (4)	15% wind, 15% solar		
EC-IAM					Y		
ENV-Linkages							Y
FARM					Y		
GCAM		Y*	Y* (either gas or battery)	Y in USA (4)			
GRAPE					Y		
IMACLIM				Y (8)	Y		
IMAGE			Y	Y			
MERGE	Y					W: 15	
MESSAGE	Y	Y	Y				
Phoenix							Y
POLES			Y		Y		
REMIND	Y	Y				W: 14-24, PV: 12-30, CSP: 8-18	
TIAM-WORLD				Y (6+1)			
WITCH	Y						

Table S4.3: Overview of system integration mechanisms in the EMF27 models.

References

De Castro C, Mediavilla M, Miguel LJ, Frechoso F (2011) Global wind power potential: Physical and technological limits. Energy Policy 39:6677–6682. doi:10.1016/j.enpol.2011.06.027.

EEA (2009) Europe's onshore and offshore wind energy potential. European Environment Agency (EEA), Copenhagen. http://www.eea.europa.eu/publications/europes-onshore-and-offshore-wind-energy-potential.

Held AM (2010) Modelling the Future Development of Renewable Energy Technologies in the European Electricity Sector Using Agent-based Simulation.

Hoogwijk MM (2004) On the global and regional potential of renewable energy sources.

Hoogwijk M, Graus W (2008) Global Potential Of Renewable Energy Sources: A Literature Assessment. Ecofys. http://www.ren21.net/pdf/REN21_RE_Potentials_and_Cost_Background_document.pdf.

Kyle GP, Smith SJ, Wise MA, Lurz JP, Barrie D (2007) Long-Term Modeling of Wind Energy in the United States. Pacific Northwest National Laboratory. http://www.pnl.gov/main/publications/external/technical_reports/PNNL-16316.pdf.

McElroy MB, Lu X, Nielsen CP, Wang Y (2009) Potential for Wind-Generated Electricity in China. Science 325:1378–1380. doi:10.1126/science.1175706.

Trieb F, Schillings C, O'Sullivan M, Pregger T, Hoyer-Klick C (2009) Global Potential of Concentrating Solar Power. Conference Proceedings, SolarPACES 2009. http://www.dlr.de/tt/en/Portaldata/41/Resources/dokumente/institut/system/projects/reaccess/DNI-Atlas-SP-Berlin_20090915-04-Final-Colour.pdf.

Tzscheutschler P (2005) Globales technisches Potenzial solarthermischer Stromerzeugung (EEMV mbH, Ed.). Lehrstuhl für Energiewirtschaft und Anwendungstechnik, TU München.

Chapter 4

Using the sun to decarbonize the power sector: the economic potential of photovoltaics and concentrating solar power *

Robert Carl Pietzcker
Daniel Stetter
Susanne Manger
Gunnar Luderer

*published in *Applied Energy* as Pietzcker, R.C., Stetter, D., Manger, S. and Luderer, G. (2014) "Using the sun to decarbonize the power sector: the economic potential of photovoltaics and concentrating solar power".
Volume 135, 15 December 2014, Pages 704–720
dx.doi.org/10.1016/j.apenergy.2014.08.011

Applied Energy 135 (2014) 704–720

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Using the sun to decarbonize the power sector: The economic potential of photovoltaics and concentrating solar power ☆

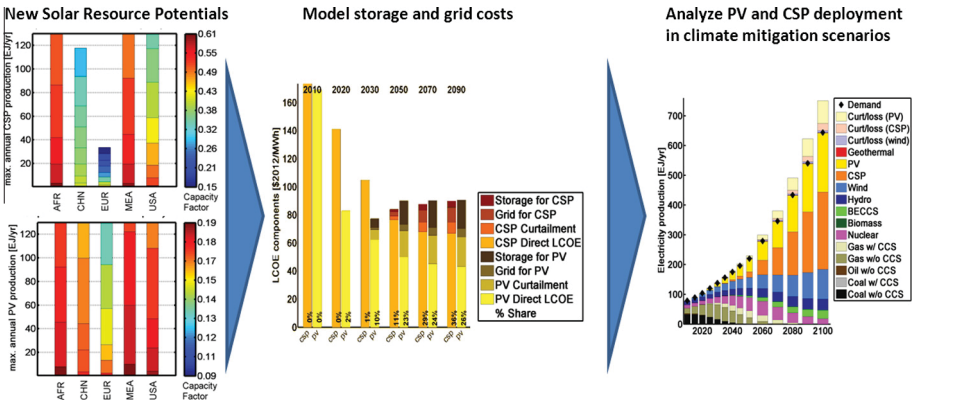
Robert Carl Pietzcker [a,*], Daniel Stetter [b], Susanne Manger [c], Gunnar Luderer [a]

[a] Potsdam Institute for Climate Impact Research, 14412 Potsdam, Germany
[b] DLR-German Aerospace Center, Pfaffenwaldring 38-40, 70569 Stuttgart, Germany
[c] Technische Universität Berlin, Straße des 17. Juni 135, 10623 Berlin, Germany

HIGHLIGHTS

- We calculate a consistent global resource potential dataset for PV and CSP.
- We develop a simplified representation of system integration costs of wind and solar.
- We analyze the economic potential of PV & CSP with the energy-economy-model REMIND.
- Solar power produces 48% of the cumulated 2010–2100 electricity in a 2 °C scenario.
- PV is deployed first, but CSP catches up due to lower system integration costs.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 6 December 2013
Received in revised form 9 July 2014
Accepted 1 August 2014
Available online 5 September 2014

Keywords:
Solar power
Variable renewable electricity
System integration
Energy system modeling
Solar resource potential
Storage

ABSTRACT

Photovoltaics (PV) has recently undergone impressive growth and substantial cost decreases, while deployment for concentrating solar power (CSP) has been much slower. As the share of PV rises, the challenge of system integration will increase. This favors CSP, which can be combined with thermal storage and co-firing to reduce variability. It is thus an open question how important solar power will be for achieving climate mitigation targets, and which solar technology will be dominant in the long-term.

We address these questions with the state-of-the-art integrated energy-economy-climate model REMIND 1.5, which embodies an advanced representation of the most important drivers of solar deployment. We derive up-to-date values for current and future costs of solar technologies. We calculate a consistent global resource potential dataset for both CSP and PV, aggregated to country-level. We also present a simplified representation of system integration costs of variable renewable energies, suitable for large-scale energy-economy-models. Finally, we calculate a large number of scenarios and perform a sensitivity study to analyze how robust our results are towards future cost reductions of PV and CSP.

The results show that solar power becomes the dominant electricity source in a scenario limiting global warming to 2 °C, with PV and CSP together supplying 48% of total 2010–2100 electricity. Solar technologies have a stabilizing effect on electricity price: if both solar technologies are excluded in a climate policy scenario, electricity prices rise much higher than in the case with full technology availability. We also

☆ This paper is included in the Special Issue of Sustainable Development of Energy, Water and Environment Systems edited by Prof. Neven Duic and Prof. Jiri Klemeš.

* Corresponding author. Present address: Potsdam Institute for Climate Impact Research, P.O. Box 60 12 03, D-14412 Potsdam, Germany. Tel.: +49 331 288 2404.
E-mail address: pietzcker@pik-potsdam.de (R.C. Pietzcker).

http://dx.doi.org/10.1016/j.apenergy.2014.08.011
0306-2619/© 2014 Elsevier Ltd. All rights reserved.

analyze the competition between PV and CSP: PV is cheaper on a direct technology basis and is thus deployed earlier, but at high supply shares the PV integration costs become so high that CSP gains a competitive advantage and is rapidly developed, eventually overtaking PV. Even in the most pessimistic scenario of our sensitivity study with no further cost reductions, CSP and PV still supply 19% of 2010–2100 electricity. We conclude that if a stringent climate target of 2 °C is to be met cost-efficiently, solar power will play a paramount role in the long-term transformation of the electricity system.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

In the last decade, photovoltaic (PV) has seen an unprecedented boom. Driven by feed-in tariffs in many countries, deployment both at residential and utility scale has risen at a remarkable pace, leading to a hundred-fold increase of the global PV market from 2000 to 2011 [1] and a cumulative capacity[1] of ~140 GW in 2013. Although silicon shortages lead to temporary price increases between 2005 and 2010 [2,3], PV has seen continual price decreases over the last 40 years, resulting in a price drop by more than 85% in the last 25 years [4]. In contrast, concentrating solar thermal power (CSP) has seen a much slower growth. After the construction of the 354 MW SEGS plants from 1981–1991, commercial deployment only restarted in 2007, leading to a 2012 global capacity estimated at 2.5 GW [5].

During the same period, climate mitigation has become an increasingly prominent item on the international agenda, with the goal of limiting global warming below 2 °C above pre-industrial temperatures. Achieving this goal requires a fundamental restructuring of the global energy system, with most studies pointing to the electricity sector as the first mover [6–11]. A large number of technologies potentially allow to produce low-carbon electricity, but most of them face technical, economical or societal risks that may slow or hinder a substantial scale-up – be it public opposition to CCS and nuclear power, limited resource potential to expand hydropower, sustainability issues and competition from the transport sector for biomass, or noise and nature conservation concerns about wind power.

Given these developments and the restrictions on other low-carbon power sources, two questions come to mind: What is the role of solar power for decarbonizing the electricity sector? And second: Have the impressive reductions of PV capital costs decided the competition between PV and CSP in favor of PV, or might CSP see resurgence and become more important in the future?

This study sets out to answer these questions with the help of the global, long-term energy-economy-climate model REMIND. Since this requires up-to-date knowledge about technology costs and resource potentials, as well as a representation of the relevant integration challenges, we augmented the model in several aspects. First, we develop a novel approach for including integration costs associated with both temporal variability and spatial heterogeneity of variable renewable energies (VRE) into large-scale energy-economy models. Second, we derive updated technology costs and learning parameters based on a comprehensive survey of the techno-economic literature on both technologies. Finally, we also develop a new and consistent global data set of resource potential data for PV and CSP.

Using the augmented model, we perform a large number of scenario runs to investigate the deployment of solar power under various cost assumptions and to determine the relevance of solar technologies for the power sector. For a deeper understanding of the role of solar technologies, we analyze several metrics, namely amount of electricity production, influence on electricity price, levelized costs of electricity (LCOE) and share in total cumulated electricity production.

There have been numerous studies analyzing the importance of solar technologies that have either focused exclusively on CSP [12–14] or PV [16,17]. Other studies have performed a comparison purely based on LCOE analysis [18–21], or have limited their analysis to only one region [22–26], and most of the studies have not explicitly looked at scenarios without climate policy.

Our study improves the understanding of the economic potential of solar power along several dimensions. Firstly, REMIND calculates inter-temporal optimal technology investment paths, taking into account all costs for investment, fuel, and emissions of the complete technology portfolio. The model fully accounts for endogenous technological learning, thus the competition for capital between the two technologies is captured within the model. While some energy-economy models include both solar technologies, they usually do not model the competition for installation sites with high solar irradiation. Finally, an important characteristic differentiating PV and CSP is the possibility of CSP to use thermal storage and co-firing of gas or hydrogen, thus capable of providing both dispatchability and firm capacity and thereby reducing the need for additional electricity storage. For a sensible analysis, a model needs to internalize this crucial difference between the integration challenges for PV and CSP, as was implemented in REMIND.

The paper proceeds as follows: We start by discussing the basic design setup in Section 2, including a description of the REMIND model and the scenario design. In Section 3, an approach for representing integration costs of variable renewable energies in large-scale energy-economic models is presented. In Section 4, current and future costs for PV and CSP are derived, while a consistent resource potential dataset for PV and CSP is calculated in Section 5. Section 6 presents and analyzes the REMIND scenario results, while Section 7 concludes.

2. Study design

In this section, we present the building blocks that we need to analyze the role of solar technologies for the decarbonization of the power sector. We start with a brief technology description to acquaint the reader with the relevant characteristics of PV and CSP, and then sketch the main features of the REMIND model that was used to explore future energy systems. We describe the scenario groups that we employ to understand the effects of solar power on the energy system and to analyze the robustness of the results. Finally, we discuss the calculation of a metric relevant for the analysis, namely levelized cost of electricity.

2.1. Solar power technology description

Solar energy can be converted directly into electricity using PV, or indirectly using thermal CSP plants. In the following we briefly describe the main characteristics of these two classes of solar

[1] "Cumulative capacity" is the sum over all capacity that was ever installed – thus cumulative capacity increases monotonously, while capacity can increase or decrease over time, as capacities are newly built or retired.

power technologies, for more detailed technology information on CSP we refer the reader to [27–30], for PV to [31,32]. The paper focuses on a generalized PV and a generalized CSP technology, without differentiating between the large variety of sub-technologies (e.g., crystallized silicon vs. thin film for PV, or trough vs. tower technologies for CSP). The sub-technologies share the same defining technological characteristics as far as the modeling framework is concerned, and the generalized long-term learning curves utilized in integrated assessment models (IAMs) incorporate the switch to cheaper sub-technologies within the same technology class.

PV cells generally employ semiconductor materials to harness the photoelectric effect. Better understanding of materials and device properties has resulted in continually increasing cell efficiencies. PV power generation is easily scalable to adapt to local requirements: for instance, decentral powering of water pumps is possible using single modules with 200 W capacity, while the modules can also be combined into vast arrays (power plants with capacities up to 250 MW have been constructed) for grid-connected operation. Also, PV modules can be placed on roofs or integrated into the building structure, thus allowing power production close to demand and tapping into a resource potential that cannot be used by other energy technologies.

CSP technologies use focusing optics like mirrors to concentrate sunlight on an absorber to heat the contained heat transfer medium to temperatures of 400–1000 °C. The thermal energy can either be directly used to generate electricity via steam turbines – as done in any conventional steam cycle process – or be stored to allow transformation into electricity at a later time. Most current CSP designs incorporate a natural gas burner for times of insufficient solar thermal energy supply as well as for heat fluid freeze protection.[2] The combination of thermal storage and gas co-firing makes CSP plants fully dispatchable while strongly reducing emissions compared to a natural gas power plant.

The two main types of large-scale CSP systems are trough systems and power tower systems. A trough system uses either long, parabolic mirrors or Fresnel mirrors constructed from many flat mirrors positioned at different angles to focus solar radiation on a line absorber that is heated to 400–600 °C. A power tower system consists of a large field of mirrors (heliostats), concentrating sunlight onto a point-like receiver at the top of a tower, thus producing higher intensities and heating the working fluid up to or above 1000 °C.

When a CSP plant is combined with thermal storage, the size of the solar field is usually increased relative to the generator size to generate enough solar thermal energy [33–35]. This is measured in "solar multiples" (SM): A CSP plant with SM1 generates enough heat at reference irradiance to run the turbine at nominal power, while a CSP plant with SM3 has a three times larger solar field and thus supplies three times the heat. If such a plant is combined with thermal storage units, the additional heat can be stored to allow full turbine operation for hours after irradiance levels drop below normal operation values. This substantially increases the capacity factor, so that a CSP plant with SM4 and 18 h of storage can reach a capacity factor similar to a base load plant. In future energy systems with high shares of CSP plants, CSP plants will also need to be designed as intermediate plants, thus using less storage and a lower solar multiple. In general, the LCOE of CSP plants with optimum storage/SM ratios does not change substantially between 6 and 12 h of storage [34,36]. As intermediate plants usually have substantially higher marginal costs than base load plants, this niche market might help the market penetration of CSP [37].

[2] Until December 2012, the Spanish feed-in tariff allowed for a 15% co-firing of natural gas with full remuneration.

Although CSP plants always require some fresh water for cleaning of mirrors, it is possible to reduce the water consumption by about 90% by using a dry-cooling design if the CSP plant is built in a location with scarce water resources [38]. However, dry cooling reduces electricity production by around 7%, equivalent to a decrease of thermal conversion efficiencies by 2–3 percentage points relative to a design with water cooling [39].

2.2. Model description: REMIND 1.5

The energy-economy-climate model REMIND is a Ramsey-type general equilibrium growth model of the macro-economy in which inter-temporal global welfare is maximized, with a technology-rich representation of the energy system [40–42]. It represents capacity stocks of more than 50 conventional and low-carbon energy conversion technologies, including technologies for generating negative emissions by combining bioenergy use with carbon capture and storage (BECCS). REMIND accounts for relevant path-dependencies, such as the build-up of long-lived capital stocks, as well as learning-by-doing effects and inertias in the up-scaling of innovative technologies. REMIND represents 11 world regions, and operates in time-steps of five years for the period from 2005 to 2060, and ten years for the rest of the century. A detailed description can be found in the published model documentation [43].

2.2.1. Technological learning

To model technology development of comparatively novel technologies with substantial scope for further technology and cost improvement, like wind, PV and CSP, we use a one-factor learning curve to represent learning-by-doing [44–48]: costs decrease according to a power law as cumulative globally installed capacity increases.

To reflect that learning slows down as a technology matures as well as the existence of thermodynamic limits and minimum material requirements, we modified this commonly used relationship by splitting investment costs into learning costs and floor costs as shown in Eq. (1). One part of the initial investment costs can be reduced through the normal learning curve, while the floor cost specify the minimum costs that are reached asymptotically at very high cumulative capacities. Thus, total learning slows down as the floor costs are approached.

$$\mathrm{IC}(\text{cumulative capacity}) = \mathrm{FC} + \mathrm{IICL} * \left(\frac{\text{cumulative capacity}}{\text{initial capacity}}\right)^{\ln(1-\mathrm{pLR})/\ln 2} \quad (1)$$

with IC the investment costs at a given cumulative capacity, FC the floor costs, IICL the part of the initial investment costs that is reducible through learning, and pLR the partial learn rate.[3]

2.3. Description of scenario ensembles

To explore the two main research questions, namely the role of solar technologies for future power sectors and if either PV or CSP clearly dominates the other technology, we run a number of different scenarios: The two basic policy settings are "reference" (REF), a scenario in which no climate policy is enacted, and "policy" (POL), in which full global climate policy is enacted by 2015. This climate

[3] It should be noted that when calculating the partial learn rate with Eq. (1) from total system costs at different capacities, the resulting value is higher than the system learn rate that would be calculated from an equation without floor costs, as the learn rate in Eq. (1) applies only to a fraction of total costs. This ensures that initial cost improvements are in line with historic trends (see Section 4 and Fig. 2).

policy is represented in the model through a global GHG budget of 2500 Gt CO_2eq for the period 2005–2100, which is roughly equivalent to a two-thirds chance of staying below 2° global warming [42].

To analyze the influence of one technology on a crucial metric such as electricity prices, we furthermore run scenarios in which we excluded the solar power technologies. In these scenarios, investments into PV and/or CSP are excluded after 2015. Removing solar power technologies from the portfolio of mitigation options leads to a different energy system and higher costs, as the reliance on other technologies increases. These scenarios reveal the economic value of these technologies for the energy system. Finally, to test the robustness of our results, we run a large number of scenarios in which we vary the future reductions of PV and CSP investment costs.

2.4. Levelized costs of electricity – direct and integration costs

Average and marginal LCOEs are important diagnostic indicators that help to understand the economic competition between the solar technologies. While LCOEs are a commonly used metric to evaluate power technologies, it is important to specify the different input assumptions that influence the calculated LCOE [49]. For marginal costs, we use build-time investment, fuel and carbon costs, build-time capacity factors of the worst resource grade that is used for this renewable technology, as well as technology-specific lifetimes. For average LCOEs, we use the investment costs that were seen when building the capacity standing at one point of time – thus, marginal costs can be lower than average costs for learning technologies whose investment costs decrease. For the LCOE calculation, we assume a real discount rate of 5.5%, which is close to the model-internal discount rate that varies between 5% and 6%.

To be able to analyze the impact of integration constraints due to the variability of solar irradiance, we also calculate the three LCOE markups resulting from the implemented integration and transmission requirements (see Sections 3.1 and 3.2) ex-post after a model run: (a) the markup from curtailment and storage losses, (b) the markup from investment costs for storage and (c) the markup from investment costs for transmission grid extension. Through analysis of these markups, it is possible to understand the trade-off between integration challenges and direct technology costs.

2.5. Limitations

As any modeling exercise, our analysis comes with limitations. Due to the long-term nature of climate change, mitigation scenarios need to extend far into the future. Technology projections are inherently risky and limited by current knowledge and imagination. The aggregation into 11 world regions omits details interesting to national policymakers. However, technology development and diffusion happen on a global scale, thus large-scale global models are required for answering questions about long-term transformation scenarios.

On the competition between PV and CSP, additional caveats apply. Due to its scalability and the absence of moving parts requiring constant maintenance, PV could easily be used in many less-developed and remote regions to power villages not connected to a central electricity grid (island grids) [50]. Also, the scalability enables local ownership, which can be a more decisive factor for technology choice than pure cost advantage [51], especially if residential PV electricity is valued at retail instead of wholesale electricity costs ("grid parity" or "socket parity", [52,53]). At the same time, CSP can be easily combined with a thermally driven desalination plant, adding an additional incentive for water-scarce regions. Also, the combination with co-firing makes a CSP plant capable of providing services to the grid very similar to a normal gas plant, thus lowering the initial acceptance barrier PV might encounter from power system operators. Such aspects cannot be fully represented in a model the size of REMIND, but their effects can only be approximated by assuming higher or lower technology costs, as done in Section 6.4.

3. System integration costs

To analyze the role of PV and CSP in future electricity systems, it is necessary to include into the model the main technology characteristics that influence deployment. Fundamentally, electricity output from PV and CSP is heterogeneous in space and variable in time. As heterogeneity and variability happen on scales smaller than those explicitly modeled within REMIND, we develop a simplified mechanism to represent the effects of both characteristics within the model. This mechanism is very generic, and thus easily transferrable to other aggregated energy-economy models. The exact parameterization can be updated as new research about costs and limitations of flexibility options becomes available, and better data availability allows better regionalization of storage and grid requirements.

3.1. Storage

PV and wind turbines depend on renewable energy sources whose incidence is variable, while electricity demand in the current system is quite inflexible. Once variable renewable energies (VRE) make up a large share of the electricity system, measures like more flexible power plants, storage, curtailment and demand side management (DSM) are required to match electricity supply and electricity demand. The variability happens on many different temporal and spatial scales: clouds can lead to local fluctuations on a scale of minutes to hours, day and night lead to very strong diurnal cycles for PV, synoptic-scale weather systems can lead to periods of several days to several weeks with low incidence of wind or sun, and there are substantial seasonal variations for the incidence of both wind and sun.

It should be noted that PV and CSP can actually have positive integration benefits at low deployment: in many countries with high solar irradiation, peak electricity demand occurs on summer afternoons due to electricity consumption from air conditioning. In these regions, highest electricity demand strongly coincides with maximum output from PV/CSP plants. Installation of solar power leads to substantial "peak shaving effects", thereby reducing the need for expensive peak load plants and decreasing the peak electricity prices – an effect easily observable in the change of German hourly electricity prices for summer days as 29 GW of PV were installed from 2007 to 2013 [54–57]. However, due to this price-decreasing effect, solar technologies cannot fully capitalize on the additional benefit they offer to the system – rather, consumers or utilities profit from reduced costs to provide peak electricity [58,59].

Endogenously calculating the optimal measures to integrate VRE would require very detailed temporal and spatial resolution, which would make a numerical long-term non-linear optimization model too complex for solving. We thus develop a simplified VRE integration representation in the model that combines estimates of the different integration measures (such as storage and curtailment of summer peaks) into (a) a cost penalty due to investments into storage technologies and (b) an energy penalty resulting from storage losses and curtailment. This energy penalty results in the need to install higher production capacities of this VRE to supply a certain share of total power demand, thus increasing net costs.

The requirement for these integration measures rises with the share of a VRE in the total power mix, as described in Eqs. (2)–(4). This is based on the both intuitive and observed notion that integration challenges increase with the amount of variable energy in the system [57,60–65]. As demand itself is somewhat variable, all existing electricity systems require a certain amount of flexibility. Adding a minor new fluctuating source does not have a large impact on the system, as the individual uncorrelated fluctuations only marginally increase total variability. Existing electricity systems in Germany, Denmark or the US had no major difficulty in including PV or wind shares of 5–10%. As one technology dominates the energy mix, however, its fluctuations have much more impact on the energy system and thus require more integration measures. We therefore require the model to build (and pay for) a certain amount of storage capacity, and to curtail a certain amount of the produced VRE energy. In each time step, the integration requirements for each VRE technology with a share higher than 7% are calculated in REMIND according to

$$\mathrm{TSC_Bat}_{VRE}\ [\mathrm{kW}] = \mathrm{SMSC_Bat}_{VRE}\ \left[\frac{\mathrm{kW}}{\mathrm{kWyr}}\right] * \left(\frac{\mathit{Net\ Share}_{VRE} - 7\%}{93\%}\right)^{a} * \mathit{Net\ Power}_{VRE}\ [\mathrm{kWyr}] \quad (2)$$

$$\mathrm{TSC_H2}_{VRE}\ [\mathrm{kW}] = \mathrm{SMSC_H2}_{VRE}\ \left[\frac{\mathrm{kW}}{\mathrm{kWyr}}\right] * \left(\frac{\mathit{Net\ Share}_{VRE} - 7\%}{93\%}\right)^{a} * \mathit{Net\ Power}_{VRE}\ [\mathrm{kWyr}] \quad (3)$$

$$\mathrm{TCE}_{VRE}\ [\mathrm{kWyr}] = \mathrm{SMC}_{VRE}\ \left[\frac{\mathrm{kWyr}}{\mathrm{kWyr}}\right] * \left(\frac{\mathit{Net\ Share}_{VRE} - 7\%}{93\%}\right)^{a} * \mathit{Net\ Power}_{VRE}\ [\mathrm{kWyr}] \quad (4)$$

with TSC_Bat/H2 as the total storage capacities of batteries and hydrogen storage built for this VRE, SMSC as the specific maximum storage capacity for each VRE, the net share of this VRE in total electricity generation, $a = 1$ the share exponent that determines how specific storage requirements increase with VRE share, and the net electricity produced from this VRE. In Eq. (4), TCE is the total curtailed/lost energy for this VRE, and SMC is the specific maximum curtailment for this VRE. Due to computational issues with negative integration capacities, the gains at market shares below 5–10% are not represented in REMIND but rather set to zero, thus initial deployment of solar technologies in the model might be slightly slower than if all benefits were included.

The VRE-specific parameters SMSC and SMC are based on assumptions about a mix of storage technologies that is able to deal with short-term and seasonal variability while balancing the trade-off between storage costs, the implied energy conversion losses, and curtailment. The exact values assumed in REMIND are described in Section 3.3 and in the supplementary information SI2.

The differences in integration requirements are one of the main differences between PV and CSP and are reflected in different values for the SMSC and SMC parameters: while PV sees a very strong day–night cycle and thus requires substantial short-term storage systems (like flow battery systems), CSP includes 12 h thermal storage and a solar multiple of three in the basic plant setup modeled in REMIND and can thus be run 18–24 h per day. For full dispatch capability, CSP plants can furthermore easily co-fire natural gas or hydrogen. To represent that CSP and PV are linked by the same solar resource, thus being exposed to the same seasonal variations and therefore negatively influencing the integration requirements of the other solar technology, we add 1/3rd of the net share of the linked VRE to the bracket in Eqs. (2)–(4).

3.2. Transmission grid

PV, CSP and wind parks often cannot be sited close to electricity demand, but require specific site conditions with high incidence of solar or wind energy to be economical. The feasibility of future power systems with high shares of renewable supply are therefore contingent on an increase in long-distance electricity transmission from sites with favorable renewable resources to demand centers [62,66–69]. A full representation of this aspect would require explicit modeling of individual supply and load centers in each region, which would again make a long-term non-linear optimization model like REMIND too complex for solving. The current state of knowledge about dependence of grid expansion on VRE shares is limited, with a recent literature review finding grid costs of 2–10 €/MW h at wind shares around 40% [70]. As there is a lack of comprehensive bottom-up scenarios covering different ranges of VRE shares, we here use geometric principles to develop a conservative estimation of long-distance grid costs arising from a given share of a VRE source in the electricity mix. We only calculate the *additional* cost directly related to the localized nature of VRE, and otherwise assume a fully developed AC grid which is able to distribute electricity on smaller spatial scales and whose costs only depend on total electricity demand and not on VRE deployment, and can thus be modeled as linear markups on all electricity, disregarding the generation type.

A cost-efficient approach to transporting electricity from regions with high quality VRE resources to other regions on a national to continental scale (500–4000 km) would be an overlay grid [67], ideally using high voltage direct current (HVDC) technology to minimize losses [71]. Such a grid would allow both a net energy transfer from regions with high quality VRE resources as well as balancing between regions with different temporal VRE incidence.

When the first VRE plants are built in a region that is rich in VRE incidence, the power can initially be used by the energy demand centers close by, thus no new long-distance grid is required. As more and more of the VRE resource is developed, local demand cannot take up the produced power so long-distance transmission is needed to reach more distant demand centers. Assuming that VRE sources are located along one edge of a region, like the solar resources in the South of the US, or wind resources in the north of China, the length of the needed transmission lines increases approximately linear with this VRE's share in total energy production. The requirement for new transmission grid capacity at VRE shares >7% are thus calculated according to

$$\mathrm{TGL}_{VRE}\ [\mathrm{kWkm}] = 0.5 * \mathrm{SMGL}_{VRE}\ \left[\frac{\mathrm{kWkm}}{\mathrm{kWyr}}\right] * \left(\frac{\mathit{Net\ Share}_{VRE} - 7\%}{93\%}\right)^{b} * \mathit{Net\ Power}_{VRE}\ [\mathrm{kWyr}] \quad (5)$$

with TGL the total grid length, SMGL the specific maximum grid length, the net production share of this VRE technology, $b = 1$ the share exponent that determines how specific grid requirements increase with VRE share and the net electricity produced by this VRE. The factor 0.5 results from the fact that if line length of new lines increases linearly with the production share, the average line length will be half of the maximum line length.

Differentiating SMGL by VRE technology and region allows modelers to represent the general pattern that PV resources are more evenly distributed than CSP resources, as well as differences in regions' size and homogeneity. Areas suitable for CSP partially coincide with sites suitable for PV, thus we also add 1/3rd of the net share of the linked VRE to the bracket in Eq. (5). The exact parameters used in REMIND are described below and in the supplementary information SI3.

3.3. REMIND implementation

In REMIND the integration challenge of variable renewable energies is completely attributed to each variable renewable technology. We require the model to invest into storage and reduce (curtail) VRE electricity output to represent the additional costs arising from the variability. The current parameterization is based on two storage technologies: redox flow batteries as short-term storage for day–night cycles and short-term fluctuations, and hydrogen electrolysis plus reconversion to electricity via hydrogen turbines as long-term storage. While other flexibility options exist, their potential is more limited by regional characteristics (pumped hydro power, compressed adiabatic air storage) or not yet fully researched (demand side management). As the two parameterized technologies do not fundamentally depend on specific local conditions, they could be deployed at large scale in each world region. Although the current values are based on technology costs for batteries and hydrogen, the general approach could be recalibrated to include effects of other flexibility options such as power-to-heat. The resulting storage and curtailment numbers used in REMIND are shown in Table 1, while the full parameters and background assumptions are described in the supplementary information SI2.

It should be noted that the storage technologies are modeled as technologies whose costs reduce via learning-by-doing, thus exact integration costs at a point in time depend on the capacities installed until that date. The size of this effect can be seen in Fig. 1, where the marginal integration costs for PV are displayed both for the investment costs in 2020, as well as for the investments costs in 2050 seen in the REMIND Policy scenario described below. To keep the figure readable, the resulting integration costs arising at different shares of wind and CSP are only displayed for the 2050 investment costs.

When comparing the marginal integration costs and curtailment levels resulting from our parameterization with the values reported in the literature [57,61,64,70,72], we find that they are in a similar range. A recent overview of integration cost studies by Hirth et al. [70] estimates near-to-medium term marginal wind integration costs (including profile, balancing and grid costs) of 25–35 €/MW h at 30–40% share. Our parameterization yields marginal integration costs at 30–40% wind share of 41–59 $/MW h in the short term, decreasing to 35–47 $/MW h in 2050, and thus seems a conservative estimate which likely overstates the integration costs slightly. As for the subcategory grid costs, the REMIND implementation results in marginal grid expansion costs of 10 $/MW h at 40% wind share, which is in line with the 2–10 €/MW h reported by Hirth et al. [70]. These integration costs substantially influence technology deployment, as will be discussed in Section 6.3.

3.4. Limitations

Both the storage and grid mechanisms are simplified and parameterized approaches. Their aim is to include an estimation of the monetary impact of variability of wind and solar into IAMs, not to develop new bottom-up insights about integration costs.

Our approach is a rough approximation of what would actually happen in a real electricity system; especially, it cannot explicitly capture the effect that remaining conventional capacities reduce their full load hours, which shifts the market in favor of low-capital technologies. It does, however, require substantial investments into storage, so that the resulting VRE output could be termed "dispatchable production" – therefore, while the model cannot determine endogenously the optimal cost-efficient mix of flexibility options, it includes a realistic-to-high estimate of integration costs. Both the storage and transmission grids installed for VRE in REMIND could also have a value for the rest of power system in the real world and thus lead to lower net cost increases, which is not explicitly included here.

In Eqs. (2)–(5), we assume that the average per-kW h integration constraint increases linearly with VRE share, once a threshold of 7% has been passed. It might also be that the integration constraints are more convex (concave), thus implying that the exponents a and b are larger (or smaller) than one. While the principal behavior is very intuitive – integration challenges increase with increasing VRE share – the exact behavior depends on a number of parameters that will be different for different energy systems in different regions, such as the coincidence of load, wind, and solar; geographical aspects like availability of reservoirs for pumped hydro storage; the residual energy system; resource prices; and elasticity of demand. It is thus clear that our approach cannot produce the optimal results for a given region. Rather, our aim is to include a *plausible* conservative estimation of integration challenges into IAMs to improve realism of the aggregated IAM results. Further research based on a large number of detailed bottom-up scenarios with high shares of VRE is needed to better inform the shape and parameterization of the integration requirements in the future, and to better differentiate between the challenges observed in different regions.

From the limited number of currently available studies, the exact dependence of integration challenges on VRE share seems an open question. The review by Hirth et al. [70] of profile costs for wind in different publications does not give a clear picture, but Fig. 12 in their paper is consistent with marginal integration costs rising linearly or even less than linearly in the reported range (up to 40% wind share). Denholm et al. [61] find wind and solar curtailment rising faster than linearly, but do not assume that storage size is adapted to increasing VRE shares. Here we assume that storage increases with VRE share, which would reduce the resulting curtailment and might lead to the linear behavior implemented in REMIND. In the supplementary information SI7, we discuss how REMIND results change when we vary the functional form of the grid and storage equations by using different values for the exponents a and b in Eqs. (2)–(5).

A limitation of the current approach is the reduced representation of the interaction between solar and wind. In the current approach, increasing the wind share does not change the integration constraints for solar, and vice versa – thus the two technologies are assumed to be not correlated. In reality, the correlation between the two technologies might be positive in one region and negative in another. Future work with detailed time series is needed to regionally parameterize the positive or negative correlations between wind and solar.

Another possible limitation of this approach is that integration constraints cannot explicitly take into account the current resource quality of the VRE, so the integration requirements per kW h are the same for PV electricity, not regarding if it was produced at a site with very high capacity factors or at a site with low capacity factors. Only regional differences, e.g., that PV time series in the US are better correlated with load than PV time series in Europe, can be represented.

While the current parameterization is geared towards the representation of storage, it is possible to adjust the parameters to represent other flexibility options. Future work will explore how integration costs are influenced by different assumptions about flexibility options and compare our implementation of integration challenges to other approaches, such as time slices [73] or additional capacity and flexibility equations [74].

All in all, we think that while the limitations are definitely relevant and require further in-depth analyses, they are basically second-order effects on the first-order effect of having integration costs at all. Based on the comparison with literature, the presented approach seems a reasonable approximation that is somewhat on

Table 1
REMIND parameters for storage, grid and curtailment at different market shares of the respective VRE technology.

For each 1 kW year of electricity replaced by VRE electricity production, the model would need to build on average the following amounts of capacity:		@20% share of this VRE, other VRE @0%			@40% share of this VRE, other VRE @0%		
		PV	CSP	Wind	PV	CSP	Wind
Of this VRE (PV/CSP/Wind)	(kW)	6.70	1.89	3.58	7.97	1.99	3.97
Battery	(kW)	0.24	0.00	0.17	0.60	0.00	0.44
H2 electrolyzer	(kW)	0.10	0.10	0.10	0.27	0.27	0.27
H2 turbine	(kW)	0.21	–[a]	0.21	0.53	–[a]	0.53
Curtailment/Storage losses	(kW year)	0.14	0.03	0.08	0.35	0.09	0.19
HVDC grid	(kWkm)	210	280	280	532	710	710
Assumed average resource quality:	(*FL h*)	*1490*	*4800*	*2630*	*1490*	*4800*	*2630*

[a] The assumed CSP plant setup already includes an H2 turbine for co-firing, so no additional investment is needed.

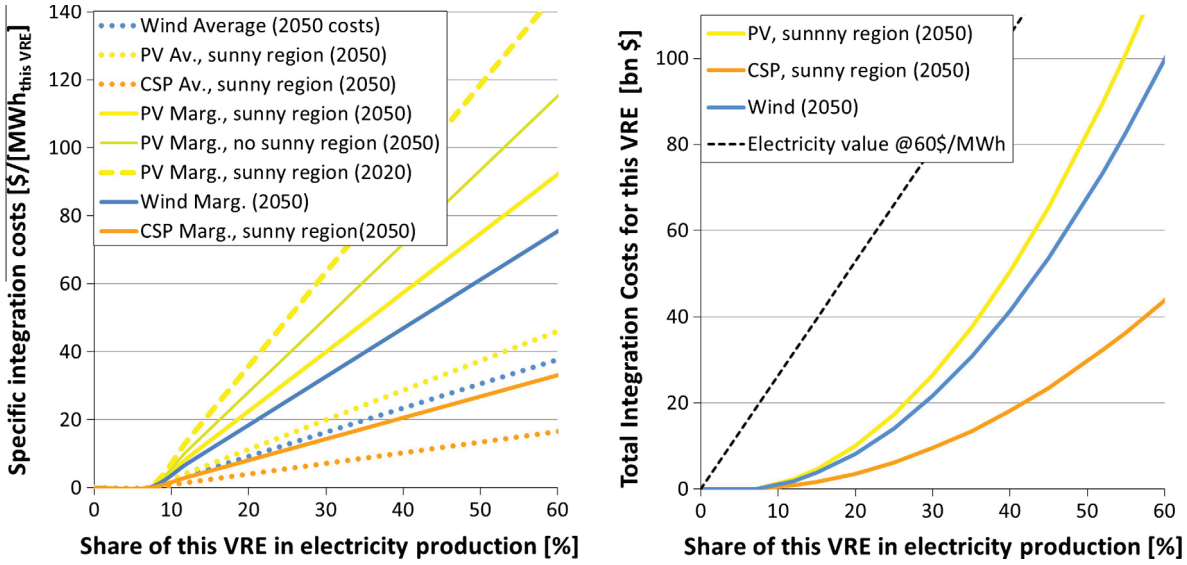


Fig. 1. REMIND integration costs for each VRE technologies as a function of this VRE's share in electricity production. Left: Average and marginal specific integration costs, assuming 2050 investment costs for storage technologies. As the share of one VRE in the power mix increases, the per-kW h integration costs rise linearly. To demonstrate the size of technological learning, we also show 2020 costs for PV. As described in SI2, the integration costs for solar are reduced for "sunny regions" where solar incidence and peak demand overlap well (Africa, Middle East/Asia, India and the US). Right: Total integration costs, assuming a total power system size of 4400 TW h, comparable to the US. As the linearly increasing per-kW h integration costs are multiplied with the produced VRE electricity, the total integration costs increase quadratic in VRE share. For comparison, the total value of the produced VRE power when valued at 60 $/MW h is also displayed.

the conservative side, possibly underestimating integration challenges in a few instances, but generally slightly overestimating them.

4. Solar power technology investment costs

The choice between technologies in energy-economy-models depends crucially on technology costs. To develop a sound basis for capital cost values, we undertook an extensive literature survey, using scientific publications, technical reports and market research. For consistency reasons, all prices need to be in the same unit and valued at the same time. Thus, all prices from literature were first converted to US dollars using the average annual exchange rate [75], and then inflated to 2012 values using the average of the US and EU CERA power plant price index without nuclear [76]. The exact assumptions for this can be found in the supplementary information SI1.

The PV boom starting at the end of the 90s spurred a large number of cost studies, and the IEA Photovoltaic Power Systems Programme [77] has annually monitored national PV system prices and markets over the last decade. As no commercial CSP plant was built between 1990 and 2007, the amount of real market data for CSP is more limited, and prices from individual installation figure more strongly in the cost analysis.

Comparing cost numbers for CSP is more complicated than for PV, as the capital costs per kW strongly depend on the amount of storage and the size of the solar field and thus need to be harmonized to be comparable. Izquierdo et al. analyzed the influence of different ratios between solar multiple and storage size and found least cost of electricity at solar multiples over 2.5 in combination with storage of 8 h and greater [34]. The basic CSP plant setup in REMIND was thus chosen to have a solar multiple of 3 and 12 h of storage. We therefore rescaled all numbers found in the literature to this setup to make them comparable.

4.1. Resulting technology costs

The collected rescaled data for overnight investment costs of PV and CSP systems is displayed in Fig. 2. For PV, the last twenty years have shown a continuously increasing amount of installations, so reliable cost figures are available that monitor the substantial price decrease. Although economic cycles (due to, e.g., scarcity of feedstock silicon that led to high PV module prices in 2005–2009) caused price fluctuations lasting for several years, over longer time

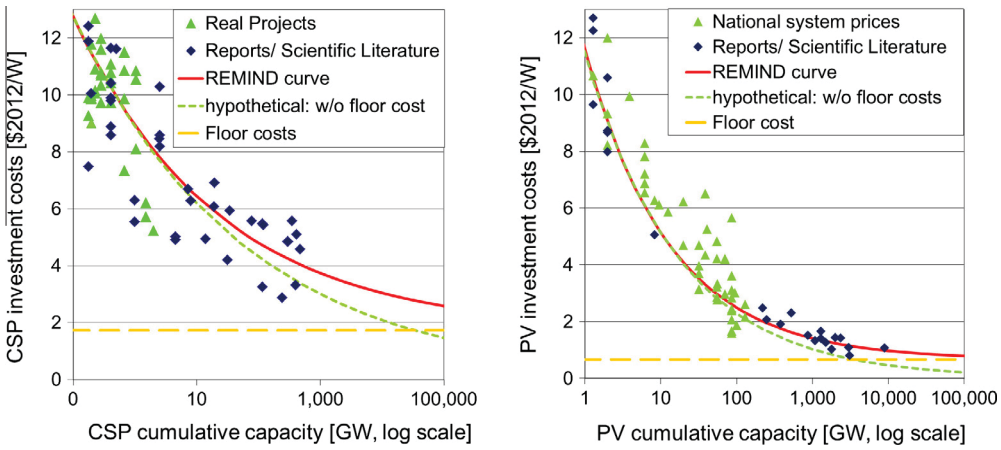


Fig. 2. Overnight investment costs for CSP (left) and PV systems, collected from national market averages, individual projects, reports and scientific publications. To reflect the model-internal CSP systems design, CSP costs are scaled to SM3 and 12 h storage, and cumulative capacity values for CSP are divided by 2. Data was collected from [2,22,25,32,77,78,82–93], with mapping of sources to individual data points presented in the supplementary information SI1.

scales PV consistently showed a very high learning rate of 20 ± 5% [2,3,47,78,79].

The numbers show a substantial cost differential between different countries: At the end of 2012, at a global cumulative capacity of ~100 GW, the total system cost for PV systems larger than 10 kW were in some countries as low as 1.6 (China), 1.3–3.3 (Italy) or 1.7–2.1 $/Wp (Germany), while other countries showed values around 3–5 $/Wp (USA) or even 5.5 $/Wp (Japan)[4] [80].

Recently, a study by the Lawrence Berkeley National Laboratory analyzed the substantial price gap between Germany and the US and found several drivers, including market fragmentation, standardization of installation procedures, amount of skilled labor required, permitting procedures, and financing impacts of remuneration policies [81].

In the current REMIND version, investment costs are not regionalized, so we derived one global investment cost value. The very low prices seen in some countries in 2012 are at least partially due to the build-up of production overcapacities at the same time as support policies were strongly reduced. This led to market shakeouts, which are often accompanied by prices below cost. On the other hand, market size and market maturity have a large decreasing influence on PV prices [78,81]. As PV markets around the world continue to develop and grow, the higher costs seen in the currently younger and smaller markets will generally converge towards the lower values seen in the currently larger and more mature markets. We thus derived a global value that is in line with the cluster of low current cost values seen in Fig. 2, with the final parameterization displayed in Table 2.

5. Solar resource potential

An assessment of future deployment of solar technologies requires data on the total resource potential for this technology in each of the modeled regions. This has been assessed by previous studies, but none of these were sufficient for our analysis: Several of these studies focus on only one of the two solar technologies [33,94], some report only aggregated global values [95], and others have aggregated the data in such a way that the substantial variations in resource *quality* (Irradiance/capacity factor (CF)/Full Load hours (FLh)) in each region are strongly suppressed [17,96] or even totally removed so that only resource *quantity* is reported [97,98].

[4] If not specified otherwise, all prices in this text are expressed in terms of US$2012.

Using data from different detailed studies for the two solar technologies is problematic, as the studies can have very different assumptions on land use and excluded areas, thereby introducing a strong artificial bias towards one of the technologies. It was thus necessary to develop new data in which both solar technologies are treated equally.

The two solar technologies use different aspects of the light: CSP can only use direct sunlight normal to the plane of incidence, termed "direct normal irradiation" (DNI), while PV cells can also use indirect – diffuse – light reflected from clouds, thus the relevant measure is "global tilt irradiation" (GTI). In general, sites with high DNI also have high GTI values, thus the two technologies compete for similar sites.

To produce new consistent resource potential data for PV and CSP, we developed a routine to derive both direct normal irradiance (DNI) and global tilt irradiance (GTI) hourly data from NASA's SRB 3.0 data [99], and calculate capacity factors for both CSP and PV (For more detail on the algorithms, see Stetter [100]). Using GIS map filters, we exclude unsuitable land and develop a potential map binned by capacity factor, countries and distance to grid. CSP plants need flat ground, while PV modules can also be installed in mountainous regions – thus a much larger land area is usable by PV than by CSP, see results presented below. The FLh for CSP were scaled to SM3 using the formula by Trieb et al. [25].

The resource potential data for PV and CSP goes beyond previous work as it (a) derives coherent resource potentials for both CSP and PV using the same solar radiation data and applying the same exclusion factors for both technologies (except for the slope as PV can be installed on much steeper terrain), (b) reports results on a national level, allowing data aggregation to various region definitions for use in other IAMs, (c) bins the resource potential by capacity factor, thus leaving all technology cost assumptions to the modeler, and (d) differentiates potential sites by distance to grid, thus allowing modelers to include markups for additional grid connection costs.

5.1. Competition for installation sites

CSP and PV compete for the sites with highest irradiation, and all sites usable for CSP can also be used for PV. It was thus necessary to implement an additional mechanism to guarantee that at no time, the model would use more than the total available land area, while still allowing the model full flexibility of allocating the land area to PV or CSP. We therefore developed a competition mapping for the land that can be used by both CSP and PV, by split-

Table 2
Technology parameters for solar technologies in REMIND.

	Overnight investment costs End 2013 $2012/Wp ($2005/Wp)[a]	Cumulative capacity End 2013 GW	Yearly O&M costs % of investment cost	Learn rate 2002–2013	Floor cost $2012/Wp ($2005/Wp)[a]	Life time years	Resulting partial learn rate in Eq. (1) (%)
PV	2.3 (1.7)	140	1.5	20	0.7 (0.5)	30	24
CSP (SM3, 12 h storage)	8.5 (6.2)	1.7[b]	2.5	10	1.7 (1.3)	30	12

[a] As the currency in REMIND is $2005, we also state the investment cost numbers in $2005.
[b] As most CSP installations until today are equipped with little or no storage, this value (and all CSP capacity values in this paper) are scaled down by a factor of two in relation to industry figures to accommodate for the SM3, 12 h storage CSP design used in REMIND.

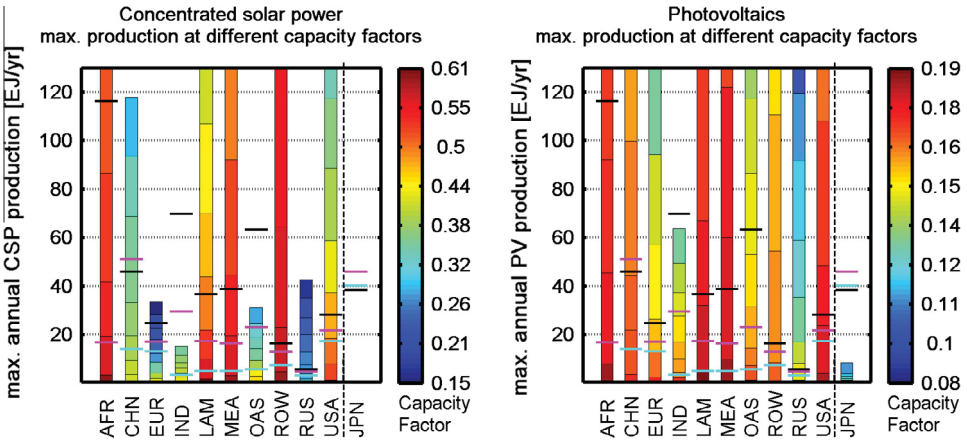


Fig. 3. Resource potential for CSP (left) and PV (right) aggregated to REMIND regions. The resource potential is binned according to capacity factor, as shown by the color coding. The three horizontal lines represent the secondary electricity production in the REF scenario: cyan in 2010, magenta in 2050, black in 2100. The energy values for Japan are upscaled by a factor of 10 to be able to display them in the same plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ting the available area into nine resource grades, ordered by resource quality. Additional information about the resource potential calculation, aggregation and land use constraints can be found in the supplementary information SI4.

To represent the competition for installation sites with good irradiation in the model, we added an additional land constraint equation. Therefore, electricity production from solar resources is limited by three equations: two equations limiting the maximum energy production for each solar technology (Eqs. (6) and (7)), and a combined equation that requires the sum of the area used by the solar technologies to be smaller than the total available land area (Eq. (8)). These equations are applied individually to each resource grade category g, in each time step.

$$\forall g: \quad \text{Available Area}_{PV,g} \geqslant \text{Cap}_{PV,g} * \text{LandUse}_{PV,g} \tag{6}$$

$$\forall g: \quad \text{Available Area}_{CSP,g} \geqslant \text{Cap}_{CSP,g} * \text{Landuse}_{CSP,g} \tag{7}$$

$$\forall g: \quad \text{Available Area}_{PV,g} \geqslant \text{Cap}_{CSP,g} * \text{Landuse}_{CSP,g} + \text{Cap}_{PV,g} * \text{Landuse}_{PV,g} \tag{8}$$

with Available Area in km^2, Cap in MW, and Landuse in km^2/MW.[5] As all areas available for CSP can also be used by PV, Available Area$_{CSP,g} \subset$ Available Area$_{PV,g}$. The Landuse values applied in REMIND are 0.009–0.017 km^2/MW for PV (regionally differentiated due to different shadowing effects of tilted installation at different latitudes, see Table 10 in the supplementary information), and 0.045 km^2/MW for CSP (latitude effects are included in the capacity factor calculation).

[5] As Cap and Landuse are always positive, Eq. (6) holds automatically when Eq. (8) holds.

5.2. Resulting resource potential data

In line with previous assessments [98], we find the total technical potential for solar electricity to be immense (see Fig. 3 for regional and supplementary information SI2 for regional and country data), surpassing today's electricity demand by a factor of more than 20 in each region except Japan.[6] Besides this obvious fact, several interesting facets can be seen in the potential data:

- For PV, each of the eleven macro-regions considered in REMIND except JPN and RUS could supply today's electricity demand by PV installations with CF > 0.17 (FL h > 1500), which are considered as good conditions that would result in comparatively low electricity costs. For comparison, average FLh values for PV plants in the south of Germany are around 950–1050.
- For CSP, the difference between regions with more and less irradiation is more pronounced: In the regions AFR, LAM, MEA, ROW and USA, today's electricity demand could be supplied by CSP installations with CF > 0.53 (FLh > 4700).
- After applying all the exclusion factors, 0.5–20% of the total land area of a region are theoretically usable for the installation of PV.
- As PV can be installed in regions with a higher slope, in all regions except for AFR and ROW more than 50% of the total usable area can only be used for PV and not for CSP.

[6] For Japan, the high population density and rough terrain lead to a very low total solar potential according to the GIS exclusion areas. To account for the potential of roof-top PV, we added conservative estimates from other sources (more information in the supplementary information SI4).

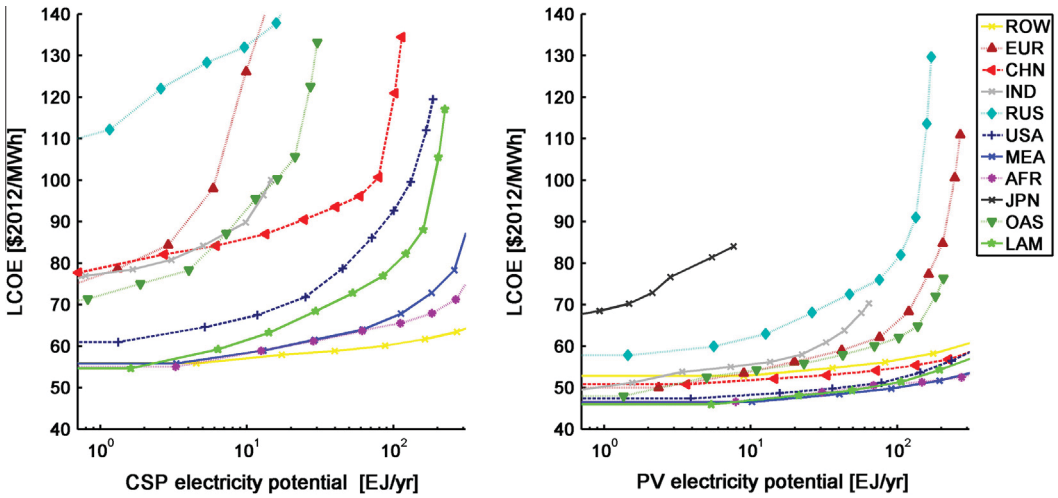


Fig. 4. Cost supply curves for CSP (left) and PV (right), assuming investment costs at 10 TW cumulative capacity for PV and 3 TW cumulative capacity for CSP. The potential for Japan is again upscaled by a factor of 10 to be visible at the given scale.

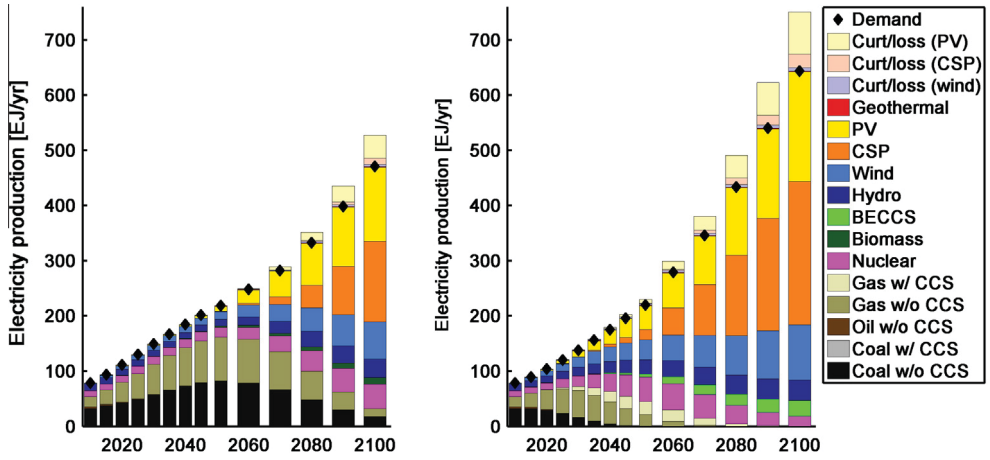


Fig. 5. Electricity Production (globally aggregated) in REF scenario (left) and POL scenario (right). The black diamond represents the net electricity that satisfies electricity demand, while the shaded "Curt/loss" represents the production from PV, CSP and wind that is either curtailed or lost due to conversion losses in electricity storage.

Compared to previous CSP potential data studies that directly use the aggregated annual NASA DNI data [33], we find lower capacity values for regions with high solar irradiance, such as the US, North Africa, or Australia. This might be the result of the processing of the radiation data, including temporal downscaling, regional aggregation, and application of a clearness index model, which leads to a mean deviation of −8% against long-run NASA annual averages, but only a −1.8% mean deviation against direct measurements from 18 ground sites, as described in [100]. At the next release of NASA satellite radiation data, the calculated values should therefore be checked against the new satellite data and against data from a larger number of ground sites. It should be noted that satellite observations are inherently different from ground measurements, and that satellite DNI estimates are quite sensitive to atmospheric parameters [101]. CSP research would benefit greatly if all existing CSP plants would publish their hourly production data.[7]

By assuming technology costs, it is possible to translate these resource potentials into supply cost curves for PV and CSP. In Fig. 4, we show the supply cost curves that result from the presented resource potentials in combination with investment costs resulting from the default REMIND learning parameters and an assumed cumulative capacity of 10 TW for PV and 3 TW for CSP.[8]

6. Scenario results

In the following, we determine the role of solar power for decarbonizing the power system by analyzing the model results from the various scenario groups along several metrics. We start with a discussion of the default scenario with and without climate policy, using the most direct metric, namely electricity generation. We then elaborate on the interplay of solar deployment and electricity price, using a scenario in which we exclude the two solar technologies. We discuss the importance of integration costs for the choice between PV and CSP. Finally, we use a large scenario ensemble with a wide range of assumptions about future cost reductions for solar technologies to test the robustness of our findings on solar deployment.

[7] As most currently-installed CSP plants are subsidized in some form or other, it should be straightforward to link the subsidy to the requirement to publish full time series of power production.

[8] These cumulative capacity values are realized in the default REMIND climate mitigation scenario between 2050 and 2060. The factor three difference between the cumulative capacities for CSP and PV reflects the different CFs.

Table 3
Capacity values, cumulative capacity values (the sum over all capacities that were ever installed) and investment costs for PV and CSP in REF and POL scenarios.

		2020	2030	2040	2050	2060	2070	2080	2090	2100
REF, global values										
CSP capacity	(GW)	1.8	1.9	3.5	26	184	810	2447	5405	9217
Cumulative CSP capacity	(GW)	2.1	2.3	4.6	29	188	824	2525	5749	10,337
CSP investment costs	($/kW)	8020	7900	7180	5620	4480	3820	3430	3190	3040
PV capacity	(GW)	296	337	524	1422	4021	8483	15,194	23,327	30,982
Cumulative PV capacity	(GW)	306	363	630	1726	4467	9403	17,558	28,861	41,565
PV investment costs	($/kW)	1950	1870	1640	1340	1120	1030	960	910	880
POL, global values										
CSP capacity	(GW)	4.1	39	259	1101	3031	5904	9565	13,463	17,374
Cumulative CSP capacity	(GW)	4.4	40	262	1119	3139	6387	11,141	17,287	24,416
CSP investment costs	($/kW)	7210	5390	4310	3710	3360	3160	3020	2920	2850
PV capacity	(GW)	480	1876	4734	8797	13,662	19,962	29,274	39,988	49,926
Cumulative PV capacity	(GW)	489	1906	4915	9628	16,194	25,779	40,188	58,179	77,694
PV investment costs	($/kW)	1620	1220	1050	960	900	860	830	810	790

6.1. Future electricity generation

To analyse the deployment of solar electricity technologies in REMIND, we show the globally aggregated electricity production in the two default scenarios in Fig. 5 and Table 3 (Regional deployment of solar technologies is displayed in the supplementary information SI6). Immediately apparent is the dominance of solar technologies in the climate policy scenario (POL), where they together account for 48% of the total electricity produced from 2010–2100. Even without climate policy (REF), PV and CSP supply a sizeable share of total electricity in the second part of the century.

In both cases, the electricity production increases steadily during the century. The energy demand is determined largely by three factors: the assumed population growth scenario (exogenous assumption), the economic growth (quasi-exogenously determined via assumptions on labor productivity growth), and the resulting electricity price calculated endogenously by REMIND. The continuous decrease of fossil fuel resources and the increase in energy efficiency counteract the general trend toward higher electrification, thus dampening the upward development of electricity consumption. The POL scenario shows higher electricity demand than REF due to stronger electrification – the power sector is easier to decarbonize than heat or liquid fuel production, so the whole energy system shifts towards electricity.

The electricity production in the REF case is dominated by fossil power plants for the next fifty years, while variable renewable energies take over in the last decades of the century. Electricity from coal and gas increases strongly in the next decades because of low resource costs and flexible trade, together supplying more than 70% of total electricity. As for renewable energies, wind supplies around 6% of yearly electricity demand until 2050, then increases due to increasing extraction costs of coal and gas. The use of solar energy only starts in the second half of the century, with the share of solar in the generation mix staying below 3% until 2050. After this late start, the deployment of solar power and wind increases strongly, so that the share of variable renewable energies surpasses 60% by 2090. As biomass is scarce and at the same time valuable for the provision of non-electric fuels for the transport and heating sectors, its share in electricity production never surpasses 3%.

In the policy scenario, drastic changes in the energy system are induced by the imposed carbon budget. While the use of fossil fuels is significantly reduced and coal is phased out completely, renewable technologies and nuclear energy are developed earlier. In contrast to the REF scenario, both PV and CSP are built immediately, so that PV reaches 8% generation share in 2030, and CSP reaches 8% in 2050. From 2055 onwards, solar technologies dominate the power mix. In 2100, the share of all non-biomass renewable technologies in the electricity mix surpasses 90%. The large-scale deployment of solar technologies in the POL scenario drives down the investment costs much earlier than in the REF scenario, as can be seen in Fig. 6 and Table 3.

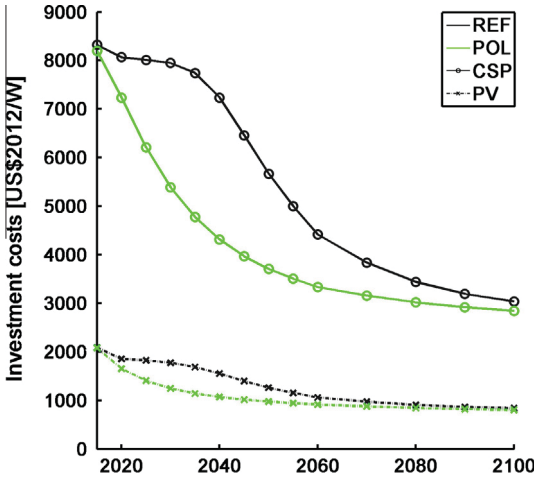


Fig. 6. Endogenous decrease of overnight investment costs for PV and CSP over time in the REF and POL scenarios due to learning-by-doing.

The substantial deployment of PV and CSP seen in the POL scenario might raise questions about potential bottlenecks to this scale-up. While a detailed analysis of this question goes beyond the scope of this paper, the following rough estimation of the most likely limiting factors shows that the presented scenarios are plausible.

Area-wise, the globally installed capacity of 50 TW of PV and 17 TW of CSP in 2100 cover an area of ~1.3 million km^2, equal to 1% of the global land area. In the US, the covered area in 2100 is ~79,000 km^2, comparable to the 73,000 km^2 used in 2009 for ethanol production from corn [102], thus land usage does not appear to be a binding limit to deployment.

From a raw material point of view, there are no clear bottlenecks currently expected for CSP. The production of certain molten salts for thermal storage might be a limiting factor, but a large number of alternative storage mediums are currently under research, with some as cheap and widely available as concrete [103]. For PV the situation is a bit different: while silicon supply is close to unlimited in the long run, the silver used for the electric contacts might be a critical input, as the silver use for PV accounted for about 7% of total silver production in 2010 [104]. On the other hand, research into replacements for silver has been ongoing for decades, and a number of research groups and companies have

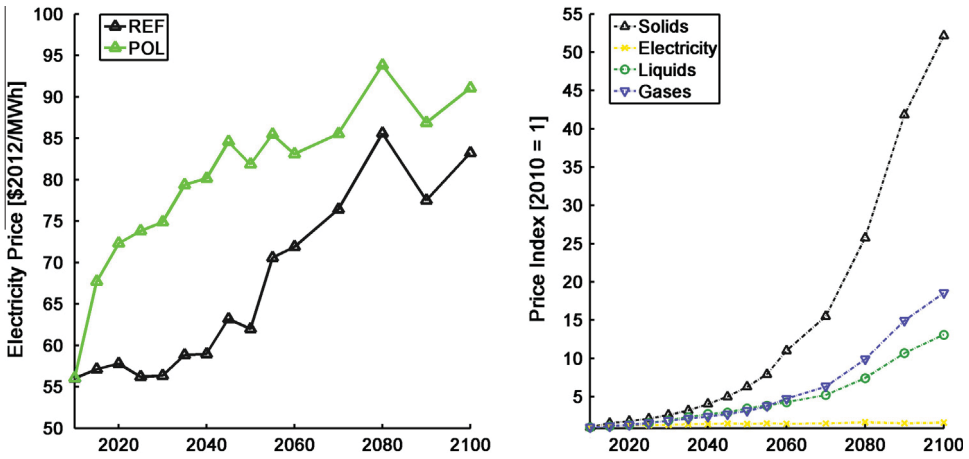


Fig. 7. Model-endogenous prices for energy carriers at power plant/refinery level (generation-weighted global average). *Left*: Electricity prices in the REF and POL scenarios. Due to interactions between the long-lived capital stocks in both electricity generation and distribution, the prices do not develop smoothly but shows some jumps up and down. *Right*: Prices of several energy carriers in the POL scenario, indexed to 2010 values. The transport sector relies mostly on liquids, while heating services are mostly provided from solids, liquids and gases.

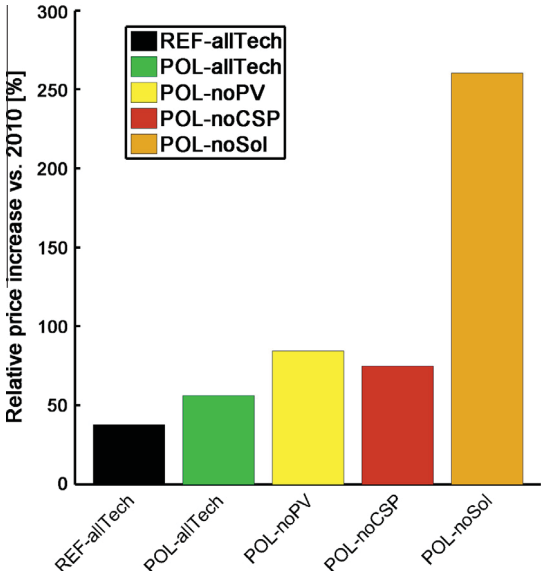


Fig. 8. Effect of excluding solar technologies on the relative increase of average 2050–2100 electricity price at the wholesale market level (generation-weighted global average) over the 2010 value.

managed to produce PV cells with Ni/Cu-contacts using industry-applicable procedures, thus presenting a possible route to widely available materials as replacement for silver [105].

Finally, the speed of the technology scale-up also seems within plausible ranges. For PV, the market growth in the scenarios slows from the historically observed annual growth rates of around 40% between 1995 and 2010 [53] to less than 15% per year after 2015. For CSP, the initial scale-up shows high annual growth rates around 25–30% per year for the first 20GW, then slows to values below 10% per year after 2050.

6.2. The impact of technologies on electricity prices

These substantial deployments show the relevance of solar technologies, but for a deeper understanding of the interactions it is instructive to compare the timing of renewable deployment with the endogenous development of electricity prices in both scenarios (see Figs. 5 and 7). In the following, all discussed energy prices are wholesale market prices, before distribution costs and taxes. In the REF scenario, the price stays close to the initial price of ~55 $/MW h until 2050, and increases due to rising resource prices to a level of ~80 $/MW h in 2080, where it remains until 2100. In the POL scenario, the carbon budget leads to a carbon price that starts in 2015 with 24 $/t CO2 and increases with the model-internal discount rate of about 5% per year. The rising carbon price immediately makes electricity from coal – and to a lesser extent gas – power plants more expensive, thereby increasing the electricity price to levels around 80 $/MW h in 2040. At this level, the electricity price is high enough to incentivize the large-scale deployment of solar technologies, which decarbonizes the electricity system and thereby slows the electricity price increase, so that the global electricity price stays in the range of 85–95 $/MW h from 2070–2100. Only regions with limited solar resources (Japan, India, and to a lesser extent OAS) see electricity prices above 110 $/MW h.

The interaction between electricity price and solar technology deployment is bi-directional: In both REF and POL scenarios, the large-scale deployment of PV and CSP is triggered as electricity prices rise above ~70 $/MW h. In return, this deployment decouples the electricity price from both resource and carbon prices: While the global coal price in REF increases 6-fold from 2010 to 2100, and the carbon price in POL increases 70-fold from 2015 to 2100, the increase of the electricity price is strongly dampened and never surpasses a level of 95 $/MW h, less than a twofold increase over 2010 values. In contrast, the other conventional energy carriers do not see such a decoupling, and all experience a more than 12-fold increase in the POL scenario, as displayed in Fig. 7.

6.2.1. Impact of technology exclusions on electricity prices

The scenarios in which the deployment of a solar technology is limited allow exploring the interaction with the electricity price in more depth.[9] Changes in electricity prices induced by exclusion of certain technologies demonstrate the relevance of that technology for the power system (Fig. 8). As discussed above, electricity prices increase even in REF until 2100 by 50% compared to 2010 due to rising resource costs. In POL, the prices increase earlier due to the carbon constraint, but do not go much higher due to the stabilizing effect of wind and solar deployment.

[9] The resulting electricity production in 2100 in the technology exclusion scenarios are displayed in the supplementary information SI5.

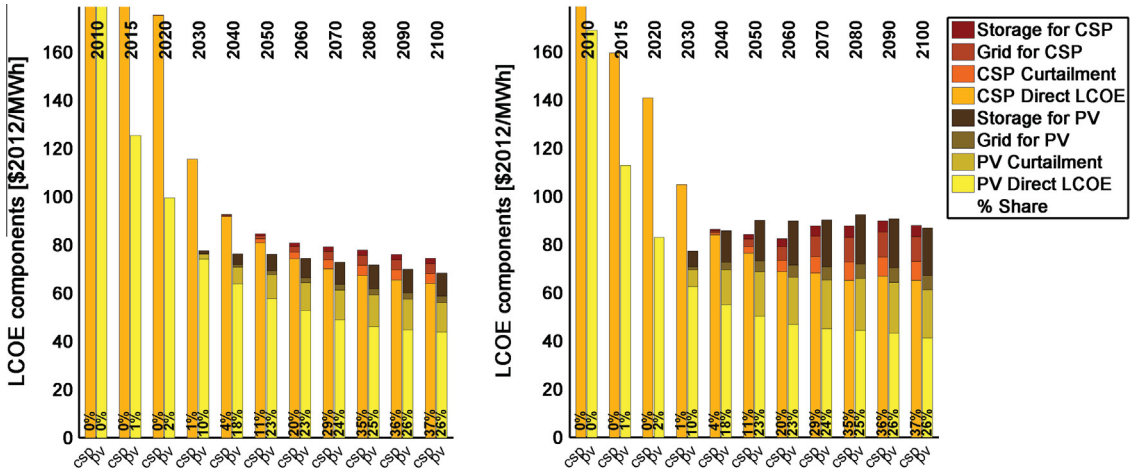


Fig. 9. Development over time of average (left) and marginal (right) System LCOE of electricity supplied by solar technologies in the USA in the POL scenario (calculated ex-post as diagnostic variable). The vertical percentage numbers display the share of this technology in total electricity generation.

In Fig. 8 we see that the decarbonization of the power sector hinges on the availability of at least one solar technology: Excluding both CSP and PV increases average 2050–2100 electricity prices by 260% over 2010. On the other hand, PV and CSP seem well capable of replacing each other should one of the two face substantial deployment barriers: excluding only *either* PV *or* CSP decreases the price increase to below 90%.

Thus, having at least one solar power technology available allows the power sector to factually decouple from scarcities in the rest of the energy system and carbon prices. While the energy carriers used for the transport sector (liquids) and provision of heat (solids, liquids, gases) face substantial difficulties when decarbonizing, leading to strongly rising energy prices in these sectors (see Fig. 7), the electricity sector can deploy large shares of solar power at only gradually rising costs, thereby slowing the electricity price increase and decoupling it from the price increase for liquids, solids or gases. If neither PV nor CSP are available, carbon prices drive electricity prices to much higher levels.

6.3. The impact of VRE integration costs on LCOE

As shown in Fig. 5, the deployment of PV precedes the deployment of CSP, but later in the century CSP becomes more important although PV investment costs are substantially below those of CSP. This behavior can be explained by the larger need for storage when deploying PV, which becomes decisive at high VRE shares. To better understand the competition between the two solar technologies, we employ the concept of System LCOE from Ueckerdt et al. [65] and analyze how VRE integration costs influence the average and marginal levelized costs of electricity production over time[10] (see Fig. 9). Put very briefly, "System LCOE" of a technology are based on the conventional LCOE measure, but try to include the monetary value of all additional effects that adding a unit of electricity from this technology has on the total system costs – including changes of required peaking plants or storage, changes of load factors of other power plants, or changes of grid requirements.

For the direct LCOE, which only depend on investment cost, operation and maintenance costs, capacity factors, life times and discount rate, the learning effect is the strongest driver. Learning-by-doing decreases the capital costs of a technology as this technology is deployed more (see Fig. 6), thus decreasing the LCOE of newly built plants. There is also a smaller counteracting effect: as more sites are used for a certain technology, the resource quality of the new sites decreases, leading to lower capacity factors, thus slowing LCOE decrease.

Besides the direct LCOE, three markups on LCOE can be calculated for VRE: the cost increase due to curtailed electricity and electricity loss in storage, due to investments into grid expansion, and due to investments into storage. The relative importance of the three integration requirements is different for the two solar technologies. Due to our assumption that PV sites are more evenly distributed across a region than CSP sites, the grid expansion costs are more relevant for CSP than for PV. On the other hand, the storage requirements and electricity losses due to curtailment are much higher for PV than for CSP.

Although the direct marginal LCOE of CSP are more than 30% higher than those of PV in every time step, the total marginal LCOE of CSP are lower than those for PV after 2040. This can be explained by the fact that the marginal integration costs of PV rise strongly as the share of PV in electricity production increases, leading to integration costs that can be higher than the direct LCOE. The impact of the integration requirements on the competition between PV and CSP can easily be observed in Fig. 9. As total marginal LCOE for CSP are lower than for PV after 2040, CSP is deployed much faster so that the CSP share eventually overtakes the share of PV. This analysis emphasizes how important it is to include the effects of VRE integration into energy economy models and not to draw conclusion solely based on direct LCOE values.

As shown in Fig. 9, the calculated cost markups on marginal LCOE become substantial once total VRE shares surpass 20–30%, especially so for PV, where additional costs from storage, grid and curtailment can become larger than direct LCOE. The ranges we calculate in REMIND are in a similar range as those calculated by Mills and Wiser [64] who analyzed how the market value of

Table 4
Maximum parameter range of learning rates and floor costs for the sensitivity study.

	PV		CSP	
	2002–2013 LR (%)	Floor cost ($/W)	2002–2013 LR (%)	Floor cost ($/W)
Expensive	16	2.2	7	7.7
Cheap	26	0	16	0.5

[10] Although it may at first seem counterintuitive, for learning technologies the marginal LCOE can be below average LCOE at a certain point in time, as the average LCOE take into account the investments that were needed to create the power system at a certain point in time. When investment costs for learning technologies decrease, the marginal LCOE decrease immediately, but average LCOE are only affected with a delay as most of the currently standing plants were built at earlier times with higher investment costs.

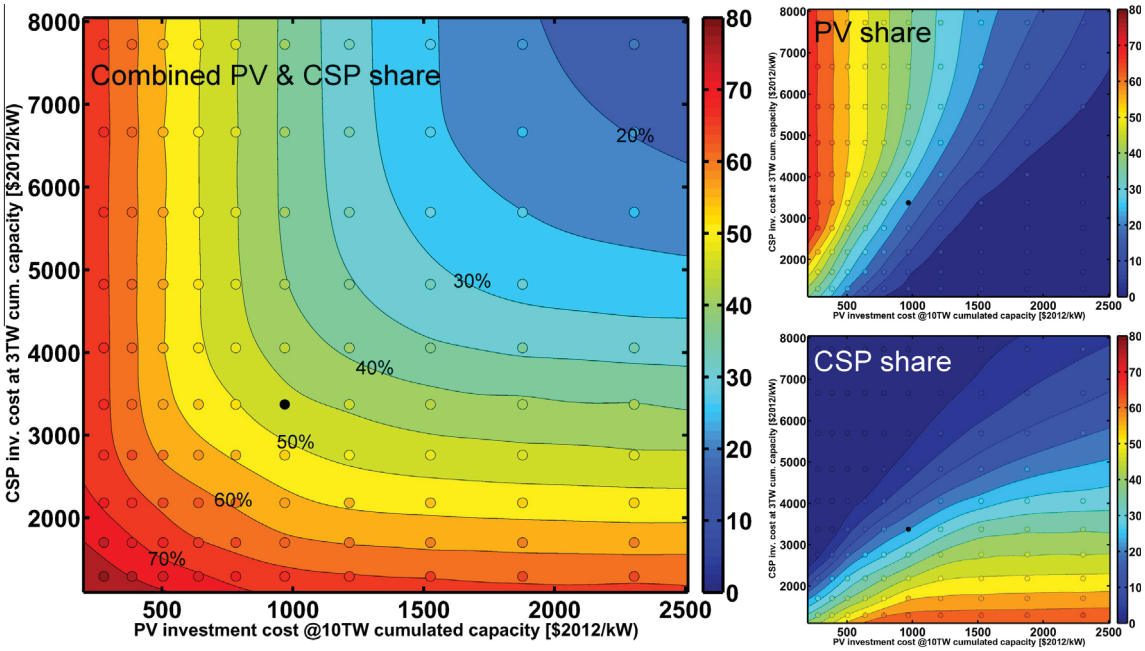


Fig. 10. Share of solar/PV/CSP electricity in total cumulated electricity production 2010–2100 at different future investment costs. The investment costs for CSP (always on the *y*-axis) are given at a cumulative capacity of 3 TW, for PV (always on the *x*-axis) at a cumulative capacity of 10 TW to account for the factor three difference in capacity factors. The open circles mark the individual REMIND runs, the black circle denotes the default assumptions.

VRE in California would change as their deployment level is increased. At 30% market share, they find that the marginal economic value of PV is decreased to one third of the initial value, while for CSP with 6 h of thermal storage the value is only reduced to two-thirds. Denholm and Margolis [72] analyze the value of PV in the ERCOT market at different storage levels, finding a doubling of PV energy costs somewhere between 17% and 35% PV share, depending on assumptions of residual system flexibility and storage capacity. Apart from these studies, there is only limited literature to compare these values to: Hirth [57] performed an extensive literature research about VRE integration costs, but only very few of the studies analyzing integration costs of solar technologies look at PV shares beyond 10%.

While the exact values of integration costs are surely up to discussion and will change as knowledge improves, these comparisons make us confident that our approach is a good step for approximating VRE integration challenges in large-scale models that do not allow modelers to explicitly represent full time series of load and VRE incidence due to numeric complexity. At the same time, we acknowledge that substantial further research is needed to (a) improve the parameterization, (b) determine the impact of regionally different time series and geographies, and (c) analyze in depth the trade-off between different flexibility options like demand side management, storage, transmission grid improvement, and flexibility of the residual system. To achieve all this, more results from dedicated electricity sector model studies covering a wide range of VRE shares as well as different world regions are needed.

6.4. Sensitivity of results to cost assumptions

Both PV and CSP are implemented in REMIND as technologies that have decreasing investment costs as deployed capacity increases (see Section 2.2.1). For both PV and CSP, there are detailed engineering proposals behind the projected decreases of capital cost in the future [32,39,106,107]. Furthermore, the last 25 years have shown that substantial learning was achieved for PV technologies, leading to cost reductions of more than 85%. Still, there is uncertainty about what part of the future projected cost reductions will be achieved over what time frame. To analyse the impact of these future cost uncertainties on solar technology deployment, we performed a sensitivity study: We varied the future investment costs at a certain cumulative installed capacity[11] by changing learning rates and floor costs as displayed in Table 4. The values for the "expensive" limit were chosen such that long-term costs were slightly below today's costs, while the values for the "cheap" limit represent very optimistic assumptions.

Our scenarios show that the importance of solar power for the electricity sector under a strict mitigation target is robust. This can be seen in Fig. 10, where we display the resulting net shares of CSP and PV in the cumulated electricity production from 2010 to 2100 for the POL scenarios under the different future cost assumptions. Even for the most pessimistic cost projections, namely the unlikely case of no further learning for PV and CSP beyond the currently reached price, the share of solar in cumulated electricity production over the next century is 19%. As the costs projections are reduced and get more closer to current estimates, the solar share increases to 48% at default assumptions, and rises further to up to 78% for the most optimistic assumptions of 280 $/kW for PV and 1300 $/kW for CSP.

The sensitivity runs also confirm that PV and CSP can partially substitute for each other. At a given cost for a PV plant, an increase of future investment costs for CSP leads to less electric power production from CSP and more production from PV, and vice versa. They are imperfect substitutes, as the total share of solar electricity is reduced in this process. Both technologies coexist and contribute significantly to total electricity production over a wide range of costs.

7. Summary and conclusions

In this paper we analyzed the role of solar technologies for decarbonizing the power sector as well as the competition

[11] To reflect the factor three difference in capacity factor between CSP plants with thermal storage and PV plants, the investment costs are given for a cumulative installed capacity of 10 TW for PV and 3 TW for CSP – both of which are reached between 2050 and 2070 in the default POL scenario.

between PV and CSP using the hybrid energy-economy model REMIND. To this end, we developed the following datasets and algorithms to augment the representation of solar power technologies in large-scale energy-economy-models:

- A simplified representation of integration challenges arising from high market shares of VRE, useful for large-scale IAMs that cannot handle more detailed power system representations due to computational limitations. Through these integration requirements, models are able to value the benefit that CSP gets from thermal storage. At high VRE penetration levels, the marginal integration costs of PV can be higher than the direct technology costs, so it is crucial to include these costs.
- Estimates of current investment cost as well as future cost reductions.
- A consistent resource potential data set for the two solar technologies, suitable for use in IAMs. The data set goes beyond previous work as it (a) derives coherent resource potentials for both CSP and PV using the same algorithm and exclusion factors, (b) reports results on a national level, allowing flexible regional aggregation, (c) bins the resource potential by capacity factor, thus leaving technology cost assumptions to the modeler, and (d) differentiates potential sites by distance to grid. The resulting potential is very large: today's electricity demand could be supplied by PV at good insolation levels (>1500 FL h) in all REMIND macro-regions except Japan and Russia.

We then performed several groups of scenario ensembles and analyzed the results, using the metrics electricity generation, electricity price, levelized cost of electricity as well as share in cumulated electricity generation. The main findings are:

- Solar electricity is projected to be the main source of electricity in the second half of the century, supplying 48% of the cumulated global electricity produced from 2010–2100 in a scenario with cost-efficient mitigation policies to achieve the 2 °C target. Even without climate policy, solar becomes the main source of electricity after 2070.
- In a climate policy world, the electricity system is highly dependent on having at least one solar technology available: excluding both PV and CSP leads to substantial electricity price increases, with average 2050–2100 prices 260% higher than in 2010.
- Integration costs are highly relevant for the competition between PV and CSP: Although PV consistently has lower direct LCOE than CSP and is initially deployed faster, CSP catches up and overtakes PV at the end of the century due to lower integration costs of CSP.
- The dominance of solar technologies for the power sector is quite robust to changing cost assumptions: Even under the most pessimistic view that the projected cost decreases are not realized and investment costs remain at current levels, solar technologies produce 19% of cumulated 2010–2100 electricity in a climate mitigation scenario.
- Both technologies can partially substitute each other: In cost-optimal scenarios, PV and CSP complement each other, but if one of the two technologies faces deployment barriers, the other can strongly increase its' share in total electricity production and partially make up for the loss of the other technology.

Solar technologies could thus be characterized as a backstop technology for the power sector in most regions: they require a certain electricity price before being deployed, but then manage to decouple the electricity price from resource and carbon price increases, as they can supply large quantities of electricity in most world regions without escalating costs.

As any modeling exercise, our results come with limitations. Due to the long-term nature of climate change, mitigation scenarios need to extend far into the future. Technology projections are inherently risky and limited by current knowledge and imagination. The aggregation into 11 world regions omits details interesting to national policymakers. However, technology development and diffusion happen on a global scale, thus large-scale global models are required for answering questions about long-term transformation scenarios.

Furthermore, technology choice is influenced by many additional parameters beyond the modeled investment costs and integration challenges, such as political preferences, differing maintenance requirements, or the possibility to produce technologies locally. Such aspects cannot be fully represented in a model the size of REMIND. Nevertheless, the wide range of future investment costs at which both technologies are used in the mitigation scenario (see Section 6.4) can act as a benchmark for how large these additional effects would have to be to knock out one of the two technologies.

Despite these caveats, the current study can be seen as a conservative scenario of a future in which no unforeseen technology[12] revolutionizes our energy system: if such a world is dedicated to limiting global warming to below 2° at lowest cost, both photovoltaics and concentrating solar power will play a substantial, maybe even paramount, role in the power system.

Acknowledgements

The research leading to these results has received funding from the European Union's Seventh Framework Programme FP7/2010 under Grant agreement number 266992 (Global IQ) and European Community's Seventh Framework Programme FP7/2012 under Grant agreement n° 308329 (ADVANCE).

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2014.08.011.

References

[1] EPIA. Global market outlook for photovoltaics – 2014–2018; 2014.
[2] Junginger HM, Lako P, Lensink S, van Sark W, Weiss M. Technological learning in the energy sector, report/WAB, no. 500102017; 2008. p. 1–192.
[3] Candelise C, Winskel M, Gross RJK. The dynamics of solar PV costs and prices as a challenge for technology forecasting. Renew Sustain Energy Rev. 2013;26(October):96–107.
[4] IEA PVPS. Cost and performance trends in grid-connected photovoltaic systems and case studies. IEA, T2-06; 2007.
[5] REN21. Renewables Global status report 2013. Renewable energy policy network for the 21st century. Global status report; 2013.
[6] Fawcett AA, Calvin KV, de la Chesnaye FC, Reilly JM, Weyant JP. Overview of EMF 22 US transition scenarios. Energy Econ 2009;31(Supplement 2, no. 0):S198–211.
[7] Luderer G, Bosetti V, Jakob M, Leimbach M, Steckel J, Waisman H, et al. The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison. Clim Change 2011:1–29.
[8] Luderer G, Pietzcker RC, Kriegler E, Haller M, Bauer N. Asia's role in mitigating climate change: a technology and sector specific analysis with ReMIND-R. Energy Econ 2012;34(Supplement 3):S378–90.
[9] Pietzcker RC, Longden T, Chen W, Fu S, Kriegler E, Kyle P, Luderer G. Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models. Energy 2014;64:95–108. http://dx.doi.org/10.1016/j.energy.2013.08.059.
[10] Krey V, Luderer G, Clarke L, Kriegler E. Getting from here to there – energy technology transformation pathways in the EMF27 scenarios. Climatic Change 2014;123:369–82. http://dx.doi.org/10.1007/s10584-013-0947-5.

[12] E.g., advanced nuclear with unlimited resources and without security and waste disposal issues.

[11] Luderer G, Krey V, Calvin K, Merrick J, Mima S, Pietzcker R, Vliet JV, Wada K. The role of renewable energy in climate stabilization: results from the EMF27 scenarios. Climatic Change 2014;123:427–41. http://dx.doi.org/10.1007/s10584-013-0924-z.

[12] Blair N, Mehos M, Short W, Heimiller D. Concentrating solar deployment systems (CSDS): a new model for estimating US concentrating solar power (CSP) market potential. Preprint; 2006.

[13] Viebahn P, Lechon Y, Trieb F. The potential role of concentrated solar power (CSP) in Africa and Europe—a dynamic assessment of technology development, cost development and life cycle inventories until 2050. Energy Policy 2011;39(8):4420–30.

[14] Zhang Y, Smith SJ, Kyle GP, Stackhouse Jr PW. Modeling the potential for thermal concentrating solar power technologies. Energy Policy 2010;38(12):7884–97.

[15] Massetti E, Ricci EC. An assessment of the optimal timing and size of investments in concentrated solar power. Energy Econ 2013;38(July):186–203.

[16] van der Zwaan B, Rabl A. The learning potential of photovoltaics: implications for energy policy. Energy policy 2004;32(13):1545–54.

[17] de Vries BJM, van Vuuren DP, Hoogwijk MM. Renewable energy sources: their global potential for the first-half of the 21st century at a global level: an integrated approach. Energy Policy 2007;35(4):2590–610.

[18] Quaschning V. Technical and economical system comparison of photovoltaic and concentrating solar thermal power systems depending on annual global irradiation. Solar Energy 2004;77(2):171–8.

[19] Peters M, Schmidt TS, Wiederkehr D, Schneider M. Shedding light on solar technologies—a techno-economic assessment and its policy implications. Energy Policy 2011;39(10):6422–39.

[20] Timilsina GR, Kurdgelashvili L, Narbel PA. Solar energy: markets, economics and policies. Renew Sustain Energy Rev 2012;16(1):449–65.

[21] Hernández-Moro J, Martínez-Duart JM. Analytical model for solar PV and CSP electricity costs: present LCOE values and their future evolution. Renew Sustain Energy Rev 2013;20(April):119–32.

[22] Trieb F, Schillings C, Kronshage S, Viehbahn P. Concentrating solar power for the Mediterranean region (MED-CSP). Forschungsvorhaben Im Auftr. Auftr. Bundesminist. Für Umw. Naturschutz Reakt. BMU; 2005.

[23] Fthenakis V, Mason JE, Zweibel K. The technical, geographical, and economic feasibility for solar energy to supply the energy needs of the US. Energy Policy 2009;37(2):387–99.

[24] US Department of Energy (DOE). SunShot vision study. Washington, DC: US Department of Energy; 2012.

[25] Trieb F, Schillings C, Pregger T, O'Sullivan M. Solar electricity imports from the Middle East and North Africa to Europe. Energy Policy 2012;42:341–53.

[26] Zhang Y, Smith SJ. Long-term modeling of solar energy: analysis of concentrating solar power (CSP) and PV technologies; 2007.

[27] Mills D. Advances in solar thermal electricity technology. Solar Energy 2004;76(1–3):19–31.

[28] Fernández-García A, Zarza E, Valenzuela L, Pérez M. Parabolic-trough solar collectors and their applications. Renew Sustain Energy Rev 2010;14(7):1695–721.

[29] Zhang HL, Baeyens J, Degrève J, Cacères G. Concentrated solar power plants: review and design methodology. Renew Sustain Energy Rev 2013;22(June):466–81.

[30] Behar O, Khellaf A, Mohammedi K. A review of studies on central receiver solar thermal power plants. Renew Sustain Energy Rev 2013;23(July):12–39.

[31] El Chaar L, Lamont LA, El Zein N. Review of photovoltaic technologies. Renew Sustain Energy Rev 2011;15(5):2165–75.

[32] IEA. Technology roadmap: solar photovoltaic energy. OECD/IEA; 2013.

[33] Trieb F, Schillings C, O'Sullivan M, Pregger T, Hoyer-Klick C. Global potential of concentrating solar power. In: Proceedings of the conference on SolarPACES 2009. Berlin; 2009.

[34] Izquierdo S, Montañés C, Dopazo C, Fueyo N. Analysis of CSP plants for the definition of energy policies: the influence on electricity cost of solar multiples, capacity factors and energy storage. Energy Policy 2010;38(10):6215–21.

[35] Madaeni SH, Sioshansi R, Denholm P. How thermal energy storage enhances the economic viability of concentrating solar power. Proc IEEE 2012;100(2):335–47.

[36] Avila-Marin AL, Fernandez-Reche J, Tellez FM. Evaluation of the potential of central receiver solar power plants: configuration, optimization and trends. Appl Energy 2013;112(December):274–88.

[37] Trieb F, Müller-Steinhagen H, Kern J. Financing concentrating solar power in the Middle East and North Africa—Subsidy or investment? Energy Policy 2011;39(1):307–17.

[38] Burkhardt JJ, Heath GA, Turchi CS. Life cycle assessment of a parabolic trough concentrating solar power plant and the impacts of key design alternatives. Environ Sci Technol 2011;45(6):2457–64.

[39] IEA. Technology roadmap: concentrating solar power. OECD/IEA; 2010.

[40] Leimbach M, Bauer N, Baumstark L, Edenhofer O. Mitigation costs in a globalized world: climate policy analysis with REMIND-R. Environ Model Assess 2010;15(3):155–73.

[41] Bauer N, Brecha RJ, Luderer G. Economics of nuclear power and climate change mitigation policies. Proc Natl Acad Sci 2012;109(42):16805–10.

[42] Luderer G, Pietzcker RC, Bertram C, Kriegler E, Meinshausen M, Edenhofer O. Economic mitigation challenges: how further delay closes the door for achieving climate targets. Environ Res Lett 2013;8(3):034033.

[43] Luderer G, Leimbach M, Bauer N, Aboumahboub T, Curras TA, Baumstark L, et al. Description of the REMIND model (Version 1.5). Social Science Research Network, Rochester, NY, SSRN Scholarly Paper ID 2312844, August 2013.

[44] McDonald A, Schrattenholzer L. Learning rates for energy technologies. Energy Policy 2001;29(4):255–61.

[45] Neij L, Borup M, Blesl M, Mayer-Spohn O. Cost development—an analysis based on experience curves. Deliverable 3.3—RS1A of the NEEDS (new energy externalities development for sustainability) project; 2006.

[46] Kahouli-Brahmi S. Technological learning in energy–environment–economy modelling: a survey. Energy Policy 2008;36(1):138–62.

[47] Neij L. Cost development of future technologies for power generation—a study based on experience curves and complementary bottom-up assessments. Energy Policy 2008;36(6):2200–11.

[48] Wiesenthal T, Dowling P, Morbee J, Thiel C, Schade B, Russ P, et al. Technology learning curves for energy policy support; 2012.

[49] Branker K, Pathak MJM, Pearce JM. A review of solar photovoltaic levelized cost of electricity. Renew Sustain Energy Rev 2011;15(9):4470–82.

[50] Tsikalakis A, Tomtsi T, Hatziargyriou ND, Poullikkas A, Malamatenios C, Giakoumelos E, et al. Review of best practices of solar electricity resources applications in selected Middle East and North Africa (MENA) countries. Renew Sustain Energy Rev 2011;15(6):2838–49.

[51] Lehmann P, Creutzig F, Ehlers M-H, Friedrichsen N, Heuson C, Hirth L, et al. Carbon lock-out: advancing renewable energy policy in Europe. Energies 2012;5(12):323–54.

[52] Bazilian M, Onyeji I, Liebreich M, MacGill I, Chase J, Shah J, et al. Re-considering the economics of photovoltaic power. Renew Energy 2013;53(May):329–38.

[53] Breyer C, Gerlach A. Global overview on grid-parity. Prog Photovolt Res Appl 2013;21(1):121–36.

[54] Al-Hasan AY, Ghoneim AA, Abdullah AH. Optimizing electrical load pattern in Kuwait using grid connected photovoltaic systems. Energy Convers Manage 2004;45(4):483–94.

[55] Braun P, Rüther R. The role of grid-connected, building-integrated photovoltaic generation in commercial building energy and power loads in a warm and sunny climate. Energy Convers Manage 2010;51(12):2457–66.

[56] Bouhouras AS, Marinopoulos AG, Labridis DP, Dokopoulos PS. Installation of PV systems in Greece—reliability improvement in the transmission and distribution system. Electr Power Syst Res 2010;80(5):547–55.

[57] Hirth L. The market value of variable renewables: the effect of solar wind power variability on their relative price. Energy Econ 2013;38(July):218–36.

[58] Schaber K, Steinke F, Hamacher T. Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? Energy Policy 2012;43(April):123–35.

[59] Hirth L, Ueckerdt F. Redistribution effects of energy and climate policy: the electricity market. Energy Policy 2013;62(November):934–47.

[60] Energy GE. Western wind and solar integration study. Golden, CO: National Renewable Energy Laboratory (NREL); 2010.

[61] Denholm P, Hand M. Grid flexibility and storage required to achieve very high penetration of variable renewable electricity. Energy Policy 2011;39(3):1817–30.

[62] Mai T, Wiser R, Sandor D, Brinkman G, Heath G, Denholm P, et al. Renewable electricity futures study. Exploration of high-penetration renewable electricity futures, vol. 1. Golden, CO: National Renewable Energy Laboratory (NREL); 2012.

[63] Rasmussen MG, Andresen GB, Greiner M. Storage and balancing synergies in a fully or highly renewable pan-European power system. Energy Policy 2012;51(December):642–51.

[64] Mills A, Wiser R. Changes in the economic value of variable generation at high penetration levels: a pilot case study of California. Lawrence Berkeley National Laboratory; 2012.

[65] Ueckerdt F, Hirth L, Luderer G, Edenhofer O. System LCOE: what are the costs of variable renewables? Energy 2013;63(December):61–75.

[66] Trieb F, Schillings C, Kronshage S, Viehbahn P. Trans-Mediterranean interconnection for concentrating solar power (TRANS-CSP). Forschungsvorhaben im Auftrag des Auftrag des Bundesministeriums für Umwelt, Naturschutz und Reaktorsicherheit (BMU); 2006.

[67] Schaber K, Steinke F, Mühlich P, Hamacher T. Parametric study of variable renewable energy integration in Europe: advantages and costs of transmission grid extensions. Energy Policy 2012;42(March):498–508.

[68] Haller M, Ludig S, Bauer N. Decarbonization scenarios for the EU and MENA power system: considering spatial distribution and short term dynamics of renewable generation. Energy Policy 2012;47(August):282–90.

[69] Becker S, Rodriguez RA, Andresen GB, Schramm S, Greiner M. Transmission grid extensions during the build-up of a fully renewable pan-European electricity supply. Energy 2013.

[70] Hirth L, Ueckerdt F, Edenhofer O. Integration costs and the value of wind power. Forthcom Renew Energy 2014:64.

[71] Bahrman MP, Johnson BK. The ABCs of HVDC transmission technologies. IEEE Power Energy Mag 2007;5(2):32–44.

[72] Denholm P, Margolis RM. Evaluating the limits of solar photovoltaics (PV) in electric power systems utilizing energy storage and other enabling technologies. Energy Policy 2007;35(9):4424–33.

[73] Ludig S, Haller M, Schmid E, Bauer N. Fluctuating renewables in a long-term climate change mitigation strategy. Energy 2011;36(11):6674–85.

[74] Sullivan P, Krey V, Riahi K. Impacts of considering electric sector variability and reliability in the MESSAGE model. Energy Strategy Rev 2013;1(3):157–63.
[75] Antweiler W. Pacific exchange rate service – database retrieval system; 2013 <http://fx.sauder.ubc.ca/data.html> [accessed 23.09.13].
[76] IHS CERA. IHS CERA power capital costs index (PCCI); 2013 <http://ihsindexes.com/pcci-graph.htm> [accessed 22.09.13].
[77] IEA. IEA photovoltaic power systems programme (PVPS): national reports; 2011 <http://www.iea-pvps.org/index.php?id=93> [accessed 24.10.11].
[78] Schaeffer GJ, Alsema E, Seebregts A, Beurskens L, De Moor H, Van Sark W, et al. Learning from the sun; analysis of the use of experience curves for energy policy purposes: the case of photovoltaic power. Final report of the PHOTEX project, ECN Renewable Energy in the Built Environment, Report ECN DEGO: ECN-C–04-035; 2004.
[79] van Sark WGJHM, Alsema EA, Junginger HM, de Moor HHC, Schaeffer GJ. Accuracy of progress ratios determined from experience curves: the case of crystalline silicon photovoltaic module technology development. Prog Photovolt Res Appl 2008;16(5):441–53.
[80] IEA PVPS. TRENDS in photovoltaic applications – 2013. IEA, IEA-PVPS T1-23:2013; 2014.
[81] Seel J, Barbose G, Wiser R. Why are residential PV prices in Germany so much lower than in the United States? A scoping analysis. Lawrence Berkeley National Laboratory; 2013.
[82] Sargent & Lundy LLC Consulting Group. Assessment of parabolic trough and power tower solar technology cost and performance forecasts. Golden, Colorado: National Renewable Energy Laboratory; 2003.
[83] Keshner MS, Arya R. Study of potential cost reductions resulting from super-large-scale manufacturing of PV modules. NREL, Hewlett Packard; 2004.
[84] Viebahn P, Kronshage S, DLR F, Lechon Y. NEEDS – new energy externalities developments for sustainability, deliverable no 12.2 – RS Ia, 'Final report on technical data, costs, and life cycle inventories of solar thermal power plants,'. European Commission; 2008.
[85] Vallentin D, Viebahn P. Ökonomische Chancen für die deutsche Industrie resultierend aus einer weltweiten Verbreitung von CSP (Concentrated Solar Power)-Technologien. Studie im Auftrag von Greenpeace Deutschland, der Deutschen Gesellschaft Club of Rome und der DESERTEC Foundation; 2009.
[86] Turchi CS, Mehos M, Ho CK, Kolb GJ. Current and future costs for parabolic trough and power tower systems in the US market. In: Presented at the SolarPACES 2010; 2010.
[87] IEA. World energy outlook 2011. Paris, France: International Energy Agency; 2011.
[88] EPIA. Solar Generation 6; 2011.
[89] Ernst & Young, Fraunhofer ISI, and Fraunhofer ISE. MENA assessment of the local manufacturing potential for concentrated solar power projects. World Bank; 2011.
[90] Goodrich A, James TL, Woodhouse M. Residential, commercial, and utility-scale photovoltaic (PV) system prices in the United States: current drivers and cost-reduction opportunities. NREL Report No. TP-6A20-53347; 2012.
[91] IRENA. Renewable energy cost analysis – concentrating solar power. OECD/IRENA; 2012.
[92] Zickfeld F, Wieland A, Blohmke J, Sohm M, Yousef A, Pudlik M, et al. Desert Power 2050–perspectives on a sustainable power system for EUMENA. DII; 2012.
[93] SEIA. U.S. solar market insight 2012 year in review. GTM Research and the Solar Energy Industries Association; 2013.
[94] Hoogwijk MM. On the global and regional potential of renewable energy sources. Universiteit Utrecht, Faculteit Scheikunde; 2004.
[95] Mercure J-F, Salas P. An assessement of global energy resource economic potentials. Energy 2012;46(1):322–36.
[96] Hoogwijk M, Graus W. Global potential of renewable energy sources: a literature assessment. Backgr. Rep. Prep. Order REN21 Ecofys PECSNL072975; 2008.
[97] Krewitt W, Nienhaus K, Kleßmann C, Capone C, Stricker E, Graus W, et al. Role and potential of renewable energy and energy efficiency for global energy supply. German Aerospace Center e.V. (DLR), Ecofys, Wuppertal Institute for Climate, Environment and Energy, Report on behalf of the German Federal Environment Agency (UBA) Report-no. (UBA-FB) 001323/E; 2009.
[98] Arvizu D, Balaya P, Cabeza LF, Hollands KGT, Jäger-Waldau A, Kondo M, et al. Direct solar energy. In: Edenhofer O, Pichs-Madruga R, Sokona Y, Seyboth K, Matschoss P, Kadner S, et al., editors. IPCC special report on renewable energy sources and climate change mitigation. Cambridge University Press: Cambridge, United Kingdom and New York, NY, USA; 2011.
[99] NASA. Surface radiation budget release 3.0. National Aeronautics and Space Agency, Atmospheric Science Data Center; 2012.
[100] Stetter D. Enhancement of the REMix energy system model: global renewable energy potentials, optimized power plant siting and scenario validation. University of Stuttgart; 2014.
[101] Suri, M., Remund, J., Cebecauer, T., Hoyer-Click, C., Dumortier, D., Huld, T., Stackhouse, P., Ineichen, P., 2009. Comparison of Direct Normal Irradiation Maps for Europe. Presented at the Solar Paces 2009, Berlin, Germany.
[102] Renewable Fuels Association. Climate of opportunity – 2010 ethanol industry outlook; 2010.
[103] Kuravi S, Trahan J, Goswami DY, Rahman MM, Stefanakos EK. Thermal energy storage technologies and systems for concentrating solar power plants. Prog Energy Combust Sci 2013;39(4):285–319.
[104] Green MA. Ag requirements for silicon wafer-based solar cells. Prog Photovolt Res Appl 2011;19(8):911–6.
[105] Ur Rehman A, Lee SH. Review of the potential of the Ni/Cu plating technique for crystalline silicon solar cells. Materials 2014;7(2):1318–41.
[106] SEMI PV Group Europe. International Technology Roadmap for PV (ITRPV); 2011.
[107] Goodrich A, Hacke P, Wang Q, Sopori B, Margolis R, James TL, et al. A wafer-based monocrystalline silicon photovoltaics road map: utilizing known technology improvement opportunities for further reductions in manufacturing costs. Sol Energy Mater Sol Cells 2013;114(7):110–35.

Supplementary Information

SI 1: Solar cost data

To derive cost parameterizations for PV and CSP, we collected investment cost data from scientific papers, reports, national market reports, and individual CSP project cost reports. All cost data was first converted into US Dollar and then inflated to 2012 values using the average of the US and EU CERA power plant price index without nuclear [1]. For CSP, the data was additionally rescaled to a plant design with a solar multiple of 3 and 12h of storage.

The values depicted in Figure 1 of the main text can be found in the following tables SI Table 1-SI Table 4. The IEA PVPS reports can all be downloaded at http://www.iea-pvps.org/.

SI Table 1: CSP Investment costs from reports and scientific literature

Cumulated Capacity at SM3 setup	Specific capital cost rescaled to SM3	Source	Country	Design year	Assumed original currency	Total cost in stated currency	Total cost in 2012 values	Capacity	Storage	unscaled specific capital cost
[GW]	[$2012 /W]					[million]	[M$2012]	[MW]	[h]	[$2012 /W]
8.0	6.3	MED-CSP 2005	EU	2020	US$2000	4.0	7.3	-	16.0	7.2
350.0	5.6	MED-CSP 2005	EU	2050	US$2000	3.6	6.5	-	16.0	6.4
0.2	10.1	Vallentin 2009	EU	2007	€2008	300.0	433.8	50	7.5	8.5
34.5	5.9	Vallentin 2009	EU	2020	€2008	3.5	5.1	-	7.5	5.0
115.0	5.5	Vallentin 2009	EU	2050	€2008	3.3	4.7	-	7.5	4.6
415.0	5.1	Vallentin 2009	EU	2050	€2008	3.0	4.4	-	7.5	4.3
0.4	8.9	Enst&Young 2011	EU	2010	US$2010	364.0	383.5	50	7.5	7.5
0.2	7.5	Sargent&Lundy 2003	USA	2004	US$2002	240.0	382.2	50	12.0	7.5
1.0	5.5	Sargent&Lundy 2003	USA	2010	US$2002	534.0	850.3	150	12.0	5.5
4.5	5.0	Sargent&Lundy 2003	USA	2020	US$2002	1288.0	2050.9	400	12.0	5.0
0.2	12.4	Sargent&Lundy 2003	USA	2004	US$2002	124.0	197.4	14	16.0	14.1
1.0	6.3	Sargent&Lundy 2003	USA	2010	US$2002	461.0	734.1	100	16.0	7.2
4.5	4.9	Sargent&Lundy 2003	USA	2020	US$2002	718.0	1143.3	200	16.0	5.6
0.4	11.6	Trieb et al 2012, En. Pol.	EU	2010	US$2010	11.3	11.9	-	12.0	11.6
0.5	11.6	Trieb et al 2012, En. Pol.	EU	2010	€2010	8.5	11.9	-	12.0	11.6
19.5	6.9	Trieb et al 2012, En. Pol.	EU	2020	€2010	5.1	7.1	-	12.0	6.9
120.0	5.4	Trieb et al 2012, En. Pol.	EU	2030	€2010	4.0	5.6	-	12.0	5.4
297.5	4.8	Trieb et al 2012, En. Pol.	EU	2040	€2010	3.5	5.0	-	12.0	4.8
475.0	4.6	Trieb et al 2012, En. Pol.	EU	2050	€2010	3.3	4.7	-	12.0	4.6
14.0	4.9	IEA WEO 2011	World	2020	US$2010	3.8	4.0	-	6.0	3.9
115.0	3.3	IEA WEO 2011	World	2035	US$2010	2.5	2.6	-	6.0	2.6
0.4	8.6	Viebahn et al 2011	EU	2010	€2010	5.3	7.4	-	7.5	7.2
31.5	4.2	Viebahn et al 2011	EU	2025	€2010	3.5	4.9	-	16.0	4.8
240.0	2.9	Viebahn et al 2011	EU	2050	€2010	2.4	3.4	-	16.0	3.3
0.4	10.4	Turchi 2010	USA	2010	US$2010	800.0	842.9	100	6.0	8.2
2.5	10.3	Turchi 2010	USA	2015	US$2010	1975.0	2080.9	250	6.0	8.1
2.5	8.6	Turchi 2010	USA	2015	US$2010	660.0	695.4	100	6.0	6.8
7.3	6.7	Turchi 2010	USA	2020	US$2010	1625.0	1712.1	250	12.0	6.7
19.0	6.1	Turchi 2010	USA	2025	US$2010	1180.0	1243.3	200	12.0	6.1

0.2	11.9	Trieb 2009	EU	2005	€2008	8.4	12.1	-	12.0	11.9
2.5	8.5	Trieb 2009	EU	2015	€2008	6.0	8.6	-	12.0	8.5
77.5	5.6	Trieb 2009	EU	2030	€2008	3.9	5.7	-	12.0	5.6
300.0	4.8	Trieb 2009	EU	2050	€2008	3.4	5.0	-	12.0	4.8
2.5	8.2	IRENA 2012	World	2015	US$2010	8.5	9.0	-	14.0	8.8
0.4	9.9	IRENA 2012	World	2010	US$2010	9.6	10.1	-	12.0	9.9
0.4	9.8	IRENA 2012	World	2010	US$2010	10.5	11.1	-	15.0	10.8
400.0	3.3	DII 2012	World	2050	€2011	2.0	2.9	-	8.0	2.9

SI Table 2: CSP Investment costs from individual projects

Cumulated Capacity at SM3 setup	Specific capital cost rescaled to SM3	Project Name	Country	Design year	Currency	Total cost in stated currency	total cost in US$2012	Capacity	Storage	unscaled specific capital cost
[GW]	[$2012 /W]					[million]	[M$2012]	[MW]	[h]	[$2012 /W]
0.2	9.9	Nevada Solar 1	US	2005	US$2005	266	361.8	64	0	5.5
0.2	9.3	PS10	Spain	2005	€2005	35	58.5	10	1	5.7
0.2	9.9	Andasol1	Spain	2007	€2007	300	425.7	50	7.5	8.3
0.2	10.1	Andasol 2	Spain	2008	€2008	300	433.8	50	7.5	8.5
0.3	10.3	Andasol 3	Spain	2009	€2009	320	446.1	50	7.5	8.7
0.2	11.8	Alvarado 1	Spain	2007	€2007	236	335.9	50	0	6.6
0.2	10.0	Ibersol Puertolano	Spain	2007	€2007	200	284.7	50	0	5.6
0.2	9.0	PS20	Spain	2007	€2007	80	113.9	20	1	5.6
0.2	9.9	Extresol 1	Spain	2007	€2007	300	427.0	50	7.5	8.4
0.2	10.1	Solnova 1	Spain	2008	€2008	200	289.7	50	0	5.7
0.2	12.7	Solnova 3	Spain	2008	€2008	250	362.1	50	0	7.1
0.2	10.9	Solnova 4	Spain	2008	€2008	215	311.4	50	0	6.1
0.3	12.0	Manchasol 1	Spain	2009	€2009	370	516.8	50	7.5	10.1
0.3	17.5	gemasolar	Spain	2009	€2009	240	335.2	17	15	19.3
0.3	9.7	Astexol 2	Spain	2009	€2009	300	419.0	50	7.5	8.2
0.3	11.6	Majades	Spain	2009	€2009	237	331.0	50	0	6.5
0.3	10.7	Valle 1+2	Spain	2009	€2009	660	921.9	100	7.5	9.0
0.3	10.8	El Reboso II	Spain	2009	€2009	220	307.3	50	0	6.0
0.4	10.5	Helios 1&2	Spain	2010	€2010	430	601.1	100	0	5.9
0.4	9.7	Extresol 3	Spain	2010	€2010	300	419.4	50	7.5	8.2
0.4	10.8	Ivanpah	US	2010	US$2010	2,200	2318.8	377	0	6.0
0.4	11.1	Shams	UAE	2010	US$2010	600	632.4	100	0	6.2
0.7	10.8	Arenales	Spain	2011	€2011	314	458.3	50	7	9.0
0.4	10.4	Solana	US	2010	US$2010	2,000	2108.0	250	6	8.2
0.7	11.5	Enerstar	Spain	2011	€2011	225	328.4	50	0	6.4
0.7	7.3	Genesis Solar	US	2011	US$2011	1,000	1047.2	250	0	4.1
0.7	11.5	Mojave	US	2011	US$2012	1,600	1638.8	250	0	6.4
0.7	9.9	Crescent Dunes	US	2011	US$2011	983	1032.2	110	10	9.2
1.1	10.8	Bokpoort	S. Africa	2012	US$2012	494	505.9	50	9.5	9.9
1.5	5.7	Delingha Supcon	China	2013	CNY2013	990	163.2	50	0	3.2
1.1	8.1	Dhursar	India	2012	INR2013	21,000	462.4	100	0	4.5
1.1	10.5	Ouazarzate	Morocco	2012	€2012	900	1184.6	160	3	7.2
1.5	6.2	Rice Tower	US	2013	US$2013	800	819.1	150	8	5.3
2.0	5.2	Crossroads	US	2014	US$2013	700	716.7	150	9	4.7

SI Table 3: PV Investment costs from reports and scientific literature

Cumulated Capacity	Specific capital cost	Source	Country	Design year	Assumed original currency	Capital Cost for Residential and Commercial (in original currency)	Capital Cost for Utility (in original currency)	Assumed value (in original currency)
[GW]	[$2012 /W]					[…/W]	[…/W]	[…/W]
1.3	9.6	Schaeffer 2004: Learning from the sun	France	2000	US$2001	5.84		5.8
1.3	12.2		Germany	2000	US$2001	7.42		7.4
1.3	14.0		Netherlands	2000	US$2001	8.47		8.5
1.3	12.7		Italy	2000	US$2001	7.69		7.7
2	8.7		France	2002	US$2001	5.28		5.3
2	10.6		Germany	2002	US$2001	6.42		6.4
2	8.0		Netherlands	2002	US$2001	4.83		4.8
2	8.7		Italy	2002	US$2001	5.25		5.3
8.3	5.1	Junginger 2008	Global	2007	US$2007	5		5.0
250	2.1	IEA WEO 2011	Global	2020	US$2010		1.7-2.3	2.0
220	2.5	IEA WEO 2011	Global	2020	US$2010	2.0-2.8		2.4
1300	1.4	IEA WEO 2011	Global	2035	US$2010		1.1-1.6	1.4
1300	1.7	IEA WEO 2011	Global	2035	US$2010	1.4-2.0		1.6
380	1.9	Goodrich 2012	USA	2020	US$2012	1.7-2.3		1.9
2000	1.4	Keshner and Arya 2004	USA		US$2003	0.8-1.1		1.0
8930	1.1	Frankl 2005: NEEDS	Global	2050	€2004		0.6	0.6
2360	1.4	Frankl 2005: NEEDS	Global	2050	€2004		0.8	0.8
530	2.3	Frankl 2005: NEEDS	Global	2050	€2004		1.3	1.3
1500	1.3	IEA 2008: ETP	Global	2050	US$2007	1.24		1.2
3000	1.1	IEA 2008: ETP	Global	2050	US$2007	1.07		1.1
1080	1.3	EPIA 2011: Solar Generation IV	Global	2030	€2010	0.96		1.0
1800	1.0	EPIA 2011: Solar Generation IV	Global	2030	€2010	0.74		0.7
880	1.5	IEA 2013 PV Roadmap	Global	2030	US$2012	1.2-1.8		1.5
3100	0.8	IEA 2013 PV Roadmap	Global	2050	US$2012		0.8	0.8

SI Table 4: PV Investment costs from national PVPS reports and market reports

Cumulated Capacity	Specific capital cost	Source	Country	Design year	Currency	Capital Cost for Res&Com. (orig.currency)	Capital Cost for Utility (orig. currency)	Assumed value (orig. currency)
[GW]	[$2012 /W]					[…/W]	[…/W]	[…/W]
1.3	13.4	IEA PVPS USA 2002	USA	2000	US$2000	8-10	7.1-7.5	7.5
1.3	10.7	IEA PVPS Germany 2002	Germany	2000	€2000	6.5		6.5
2	12.0	IEA PVPS USA 2002	USA	2002	US$2002	6.5-9		7.7
2	8.2	IEA PVPS Germany 2002	Germany	2002	€2002	5.6		5.6
2	9.3	IEA PVPS Japan 2002	Japan	2002	JPY2002	720	850	750
3.9	9.9	IEA PVPS USA 2004	USA	2004	US$2004	6-9		7.0
6.2	7.8	IEA PVPS USA 2006	USA	2006	US$2006	7-8	6.5-7.5	7.0

6.2	6.5	IEA PVPS Japan 2006	Japan	2006	JPY2006	680		680
6.2	7.2	IEA PVPS Japan 2006	Japan	2006	JPY2006		750	750
6.2	8.3	IEA PVPS Italy 2006	Italy	2006	€2006	6-6.8	5-6	5.9
6.2	6.9	BSW Solar Preisindex 5/2012	Germany	2006	€2006	4.8-5.1		4.9
8.3	6.3	IEA PVPS Germany 2007	Germany	2007	€2007	4.3-4.8		4.5
9.5	6.1	IEA PVPS USA 2007	USA	2007	US$2007		5.5-7	6.0
12.6	5.9	IEA PVPS Germany 2008	Germany	2008	€2007	3.7-4.5		4.2
20	6.2	IEA PVPS Italy 2009	Italy	2009	€2009	3.5-5		4.3
20	4.7	IEA PVPS Italy 2009	Italy	2009	€2009		3-3.4	3.2
32	4.7	IEA PVPS Germany 2010	Germany	2009	€2009	3.2		3.2
32	4.0	BSW Solar Preisindex 5/2012	Germany	2010	€2010	2.9		2.9
32	3.7	IEA PVPS Germany 2010	Germany	2010	€2010	2.5-3.2		2.7
32	3.1	IEA PVPS Germany 2010	Germany	2010	€2010		2.3	2.3
39	4.3	IEA PVPS USA 2010	USA	2010	US$2010		4.2	4.2
39	6.5	IEA PVPS USA 2010	USA	2010	US$2010	5.9-6.7		6.3
41	5.3	IEA PVPS USA 2010	USA	Q42010	US$2010	5.1		5.1
55	4.8	IEA PVPS USA 2011	USA	2011	US$2011	4.7		4.7
71	4.2	IEA PVPS USA 2011	USA	Q42011	US$2011	4.08		4.1
55	2.9	IEA PVPS Germany 2011	Germany	2011	€2011	2		2.0
71	3.0	BSW Solar Preisindex 5/2012	Germany	2011	€2011	2.08		2.1
56	3.3	IEA PVPS South Korea 2011	S. Korea	2011	KRW2011	3150-4000		3600
56	2.8	IEA PVPS China 2011	China	2011	CNY2011	17.5		17.5
55	4.2	IEA PVPS Italy 2011	Italy	2011	€2011	2.5-3.4		3.0
55	3.2	IEA PVPS Italy 2011	Italy	2011	€2011		2-2.5	2.3
71	4.2	U.S. Solar Market Insight 2013	USA	Q42011	US$2011	4.1		4.1
87	5.6	IEA PVPS Japan 2012	Japan	2012	JPY2012	437-474		450
87	2.4	IEA PVPS South Korea 2012	S. Korea	2012	KRW2012	2400-3000		2700
87	2.8	IEA PVPS Italy 2012	Italy	2012	€2012	1.5-2.8		2.2
87	1.7	IEA PVPS Italy 2012	Italy	2012	€2012		1-1.6	1.3
87	2.1	IEA PVPS France 2012	France	2012	€2012		1.6	1.6
87	3.6	IEA PVPS France 2012	France	2012	€2012	2.0-3.7		2.8
87	3.1	IEA PVPS Australia 212	Australia	2012	AUD2012	3		3.0
87	2.4	BSW Preisindex 2012	Germany	2012	€2012	1.75-2.1		1.9
87	1.6	IEA PVPS China 212	China	2012	CNY2012	10		10.0
95	3.0	U.S. Solar Market Insight 2012	USA	Q42012	US$2012	3.01		3.0
100	1.9	IEA PVPS TRENDS 2013	Germany	Q42012	€2012		1.3-1.6	1.5
130	2.6	U.S. Solar Market Insight 2013	USA	Q42013	US$2013	10		2.6
130	2.2	BSW Preisindex 2013	Germany	Q42013	€2013	1.64		1.6

SI 2: Representation of storage requirements

In REMIND, the integration challenge of variable renewable energies is completely attributed to each variable renewable technology. We require the model to invest into storage and curtail VRE electricity output to represent the additional costs arising from variability. This approach is a rough approximation of what would actually happen in a real electricity system; especially, it cannot capture the effect that remaining conventional capacities reduce their full load hours. It does, however, require substantial investments into storage, so that the resulting VRE output could be termed "dispatchable production" – therefore, while the model cannot determine endogenously the optimal cost-efficient mix of flexibility options, it includes a realistic-to-high estimate of integration costs.

Although a number of different storage options currently exist or are in demonstration stage, two main classes can be differentiated: those that are potentially suited for long-term storage, such as hydrogen electrolysis or possibly power-to-heat with heat storage, and those that are only suited for short-term storage because of either high reservoir costs, such as batteries, or limited reservoir size, such as demand response or (in most places) pumped hydro storage.

As representative instances of these two classes of storage, we chose redox flow batteries (RFB)[1] for short-term storage and hydrogen electrolysis including tank storage for long-term storage. These technologies were chosen for their almost unlimited potential – other storage options like pumped hydro storage or compressed air storage require geographic settings that are limited in most regions of the world. The availability of a limited amount of cheaper storage or flexibility options would lower the cost of VRE integration at a low VRE share.

Published estimates of costs for RFB [2]–[9] and hydrogen electrolysis and storage [2], [3], [5], [10]–[12] vary widely by up to an order of magnitude. For the parameterization in REMIND, we choose the values shown in SI Table 5. For hydrogen storage costs, we decided to take values from the low end of estimates for above-ground tank storage to reflect the fact that many regions can at least partially use underground storage, which is an order of magnitude cheaper [3].

SI Table 5: Storage technology costs assumed for REMIND storage parameterization

		Hydrogen			Battery	
		electrolysis	turbine	reservoir	capacity	reservoir
Initial Cost	[$/kW] ([$/kWh] for reservoir)	1000	700	4	700	250
Floor cost	[$/kW] ([$/kWh] for reservoir)	250	400	1	250	75
Learn rate	[percent]	10%	10%	10%	10%	10%
O&M costs	[% of Capex]	2%	2%	2%	2%	2%
Life time	[year]	25	25	25	25	25

[1] In the past, mostly Lead-acid and Sodium/Sulfur batteries were deployed, but a more promising option for future large-scale battery storage are redox flow batteries (RFB) such as the vanadium redox-flow batteries currently used in several demonstration projects.

In the REMIND version employed in this work, the parameterization for the storage and grid requirements used in Eq. 2-5 in the main paper is as follows. For each VRE technology, an individual mix of battery and hydrogen storage as well as curtailment was chosen, based on the most relevant temporal variations and an estimation of what amount of seasonal variability is not cost-efficient to store and should rather be curtailed: for PV, the strong day-night cycle together with the substantial seasonal variations in output require both a large amount of short-term storage plus a sizable amount of long-term storage and curtailment. For wind, the seasonal variations are smaller than for PV, but the effect of synoptic weather patterns is more relevant, therefore sizable hydrogen capacities are required, but a smaller reservoir is sufficient. For CSP, only hydrogen electrolyzers and hydrogen storage are required, as hydrogen can be co-fired in the default CSP plant setup in REMIND, and the short-term fluctuations are smoothened by the thermal storage. The resulting REMIND parameterization of the maximum aggregate storage requirements is displayed in SI Table 6.

SI Table 6: Aggregated storage requirements in REMIND for a 100% PV, 100%Wind or 100% CSP system

		Storage per kWyear load supplied from		
	Unit	**PV**	**Wind**	**CSP**
SMSC_Bat:				
Battery capacity	[kW]	1.7	1.3	-
Total battery reservoir	[kWh]	17	8	-
SMSC_H2:				
H2 electrolysis	[kW]	0.8	0.8	0.8
H2 turbine	[kW]	1.5	1.5	-
Total H2 reservoir	[kWh]	720	360	540
SMC: Curtailment & Conversion Losses	[% of net power from this VRE]	100%	54%	33%
For information: Curtailment & Energy Losses	*[% of gross power (before curtailment) from this VRE]*	*50%*	*35%*	*25%*

The resulting integration requirements at lower VRE shares are still sizable, as displayed in SI Table 7: In a power system where 40% of a region's electricity is supplied by PV, the model will have 8kW of PV capacity and 1.1kW of storage capacity installed for each kWyear of load that is supplied by PV. The resulting electricity losses due to seasonal variation and storage losses amount to 0.35kWyears.

While the current parameterization is geared towards the representation of storage, it is possible to adjust the parameters to represent other flexibility options. Future work will explore how integration costs are influenced by different assumptions about flexibility options and compare our implementation of integration challenges to other approaches such as the one presented in Sullivan et al. [13].

SI Table 7: Effect of storage/curtailment requirements at different market shares of the respective VRE technology. (*: The assumed CSP plant setup already includes a gas/H2 turbine for co-firing, so no additional investment is needed)

For each 1kWyear of electricity replaced by VRE electricity production, the model would need to build on average the following amounts of capacity:		@20% share of this VRE			@40% share of this VRE		
		PV	**CSP**	**Wind**	**PV**	**CSP**	**Wind**
of this VRE (PV/CSP/Wind)	[kW]	6.70	1.89	3.58	7.97	1.99	3.97
Battery	[kW]	0.24	0.00	0.17	0.60	0.00	0.44
H2 electrolyzer	[kW]	0.10	0.10	0.10	0.27	0.27	0.27
H2 turbine	[kW]	0.21	-*	0.21	0.53	-*	0.53
Curtailment/ Storage Losses	[kWyear]	0.14	0.03	0.08	0.35	0.09	0.19
HVDC grid	[kWkm]	210	280	280	532	710	710
Assumed average resource quality:	*[FLh]*	*1490*	*4800*	*2630*	*1490*	*4800*	*2630*

The four “sunny” regions USA, Africa, India and Middle East/Asia are assumed to have higher seasonal overlap between (future) electricity demand due to air conditioning and solar irradiation, therefore the storage requirements are reduced by a factor of 0.8 for PV and 0.6 for CSP. The reduction is less for PV, as a large part of the PV storage costs comes from batteries, and the demand for batteries is mostly due to the day-night cycle and thus does not scale as strongly with the seasonal correlation between demand and solar irradiation as the hydrogen seasonal storage needed by both PV and CSP.

SI 3: Representation of renewable-driven expansion of long-distance power transmission

As for storage, the transmission grid expansion required when deploying variable renewable energies is completely attributed to each variable renewable technology in REMIND. We require the model to invest into additional long-distance grid, represented by high voltage DC (HVDC) lines. The specific costs for HVDC lines were derived from [14]. From maps of wind and solar resource distributions, we estimated that in each region, the maximum distance between good VRE resource and large demand centers is below 4000km[2]. For the three regions Europe, Japan and India, which are either small or which have more evenly distributed VRE potentials, grid costs are reduced by multiplying with 0.75. As PV site quality does not vary as strongly as wind and CSP site quality over a region, we assumed lower grid lengths for PV. The values in SI Table 8 are the maximum lengths, while the actually required grids scale linearly with the VRE share, as described in Eq. 5.

SI Table 8: REMIND parameters for long-distance HVDC grid transmission

		HVDC Transmission grid for		
		PV	Wind	CSP
Assumed maximum distance within one region	[km]	3000	4000	4000
Capital cost to build HVDC line of above-stated maximum length	[$/kW transmission capacity]	2700	3500	3500
Lifetime	[years]	45	45	45
O&M costs	[% of capital cost]	2%	2%	2%
SMGL - specific maximum grid length for REMIND equation	[kWkm/kWyr]	3000	4000	4000

[2] Clearly, a finer regional differentiation could be implemented, but at the limited current level of knowledge, this could give a false sense of exactness.

SI 4: Solar resource potential calculation

To derive a consistent resource potential data set with detailed Full Load hour information for PV and CSP, it is necessary to first calculate hourly direct normal irradiance (DNI) and global tilt irradiance (GTI) data. To do so, the NASA SRB 3.0 data [15] containing 3-hourly global horizontal irradiation data on a 1° grid was modified and downscaled to 1-hourly data on a 0.45° grid using a clear sky model by the DLR. Direct (or beam) normal irradiance (DNI/BNI) data was then derived from the GHI data, using an empirically fitted model of the relation between the split into direct and diffuse radiation to clearness index and optical air mass (For more detail on the algorithms, see Stetter 2013 [16]).

Photovoltaics

To calculate FLh, the GTI were reduced by 10% for losses due to dirt and conversion, and an availability factor of 98% was assumed. To include the effects of the module temperature on the PV modules, the energy production was reduced by 0.0045[1/°C] for module temperatures above 25°C. Total installable PV capacities were calculated using an installation density of $112W_{electricAC}$/m^2 at the equator, while the installation density is reduced at higher latitudes to account for shadowing effects due to tilted module installation.

Concentrating Solar Power

To calculate FLh, first the total heat output of the solar plant is calculated from the DNI and the solar elevation angle, as the lower angle of incidence at higher latitudes reduces total energy production. It is then converted to electricity assuming a thermal-to-electric conversion efficiency of 37%, an availability factor of 95%, and thermal storage efficiency of 95%. Total installable CSP capacities are calculated using an installation density of 176 $W_{thermal}/m^2$. Together with the thermal-to-electric conversion efficiency and the solar multiple of 3, this yields an installation density of 22 $W_{electric}/m^2$. It should be noted that the resulting FLh values are somewhat lower than values calculated in the past from monthly NASA DNI values. Accordingly, once more data on actual production of existing CSP plants becomes available, the calculated values should be checked against the empirical data.

The CSP Full Load hour values in SI Tables 9-11 are given for a CSP plant with a solar multiple of 3 and 12h of storage. Following the approximation in Trieb et al [17], the FLh values can be scaled to different solar multiples by multiplying with 0.363 for SM1 (no storage) or 0.725 for SM2 (6 h storage).

Suitable Areas

Using a number of GIS map filters, we excluded unsuitable land and developed a potential map binned by FLh, countries and distance to grid. Exclusion criteria were:

- all areas **not** classified as herbaceous, sparse, shrub or sparse-herbaceous shrub in the Global Land Cover database [18]. It thereby excludes all land currently used for agriculture.
- sand dunes, glaciers, salt pans
- hydrological regions such as marsh, floodplain, swamp

- protected areas
- buffer zones of 1 km around settlements
- elevation above sea level: less than 2.5 km

Furthermore, CSP plants need flat ground, while PV modules can also be installed in mountainous regions. The slope cutoff for CSP was thus set to 2.1°, while areas for PV were only excluded at slopes larger than 40° - thus a much larger land area is usable by PV than by CSP. In SI Tables 9-11, the area is always reported in three categories: competition areas that can be used both by PV and CSP, area that can be only used for PV, and all area accessible for PV, which is equal to the sum of the first to area bins:

$$\boldsymbol{Competition\ Area}\ (\boldsymbol{PV}\&\boldsymbol{CSP}) \subset \boldsymbol{Total\ PV\ Area}$$

$$\boldsymbol{Total\ PV\ Area} = \boldsymbol{PVonly\ Area} \cup \boldsymbol{Competition\ Area}\ (\boldsymbol{PV}\&\boldsymbol{CSP})$$

As the high population density and rough terrain lead to a very low total solar potential for Japan according to the GIS exclusion areas, we added the potential for roof-top PV. Estimates from other sources are in the range of 100-200 GW [19], [20]. We therefore added an installable capacity of 100 GW at 1020 FLh, which is the lowest insolation category for Japan. Other regions also have potential for roof-top PV, but we did not include it in the final data as for all other regions, it is much smaller than the GIS-based total regional potential and thus not relevant for the modeling results.

The resulting values are presented in SI Table 9, which is appended as an .xlsx file. The values are displayed for all countries with suitable area larger than 10 km^2.

Competition mapping

CSP and PV compete for the sites with highest irradiation, and as described above, all sites usable for PV are also usable for CSP. It was thus necessary to implement an additional mechanism to guarantee that at no time, the model would use more than the total available land area, while still allowing the model full flexibility of allocating the land area to PV or CSP. For this, we developed a competition mapping for the land that monitors how PV-resource quality is related to CSP-resource quality for a given plot of land. To this end, we make the basic assumption that inside one region, the land areas with the best DNI values will also have the best GTI values, thus allowing the creation of a ranked resource potential where the first 1 square km has the highest CSP and PV FLh, while the next square km would have slightly lower FLh for both technologies. As it would be numerically infeasible to track each plot of the land individually and let REMIND decide for each plot of land whether it builds PV or CSP there, we aggregated the land into nine resource grades according to resource quality. The total usable area is split into percentiles according to the quality of the resource – the first column encompasses the best percent of the area (best meaning “highest FLh”), the second column the next best 3% of the total area, and so on.

The solar resource potential is so large that the quality differences at the good end are much more relevant for most countries than the quality differences at the low end of the resource

potential. Accordingly, we used percentile bins of unequal size, with small bins for the high quality resource, and larger bins for the low-quality resource.

For each bin, the average FLh of a PV/CSP plant installed in this area is given. The resulting competition mapping on country level is presented in SI Table 11, which is appended as an .xlsx file. To improve readability of the data table, the actual amount of land that is contained in each percentile class for a given country is not displayed in SI Table 11 – to calculate it, the reader simply needs to multiply the value for "usable area" with the percentile. To calculate installable capacity per resource grade, the area in each resource grade (percentile column) has to be multiplied by the installation density (22 $W_{electric}/m^2$ for CSP, for PV the average installation density per country/region is given in SI Tables 9/10/11). To extract total power, the resulting capacities have then to be multiplied with the FLh value for their bin.

An example of how to read SI Table 11: the amount of land that falls in the category "distance to settlement: 1-50km, competition land than can be used by both PV and CSP, second percentile" in Afghanistan would be calculated by multiplying the percentile bin width (1-5%, thus 4%) with the land area in the "Usable Area: distance to settlement 1-50km" column of the work sheet "Competition map PV&CSP" both PV and CSP" category (3959 km^2), thus yielding 4% * 3959 km^2 = 158 km^2. On this land, one could install either 158 km^2 * 93 MW/ km^2 = 14694 MW PV or 158 km^2 * 22 MW/ km^2 = 3476 MW CSP. The power plants installed on these 158 km^2 would have 1740 FLh for PV and 4670 FLh for CSP, thus producing a total amount of electricity of 14.7 GW * 1740 h = 25.6 TWh from PV or 3.5 GW * 4670 h = 16.2 TWh from CSP.

REMIND input

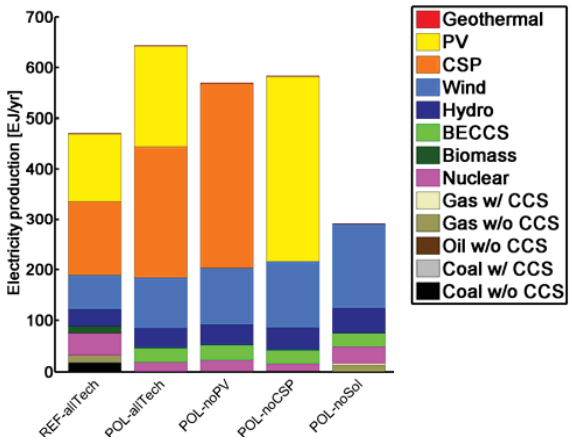
For use in REMIND, the country level data presented in SI Table 9 was aggregated to the eleven macro-regions in REMIND. Also, to reduce the number of grades and thus numerical complexity, the two distance bins (1-50 and 50-100) were aggregated into one bin: Sites closer than 50km to settlements are accounted for with full capacity factor, sites with 50-100km distance to settlements have their capacity factor reduced by 5% to account for additional grid connection costs.

To this region-aggregated data, the same competition mapping procedure as described above was applied. As the resource potential is so large, the percentile bins used are very narrow at the high irradiations end of the scale: 0.5%/ 2.4%/ 3.2%/ 7.8%/ 9.9%/ 15.9%/ 15.1%/ 20.1%/ 25.1%.

The regionally aggregated input data for REMIND is presented in SI Table 10, which is appended as an .xlsx file.

SI 5: Electricity production in technology exclusion scenarios

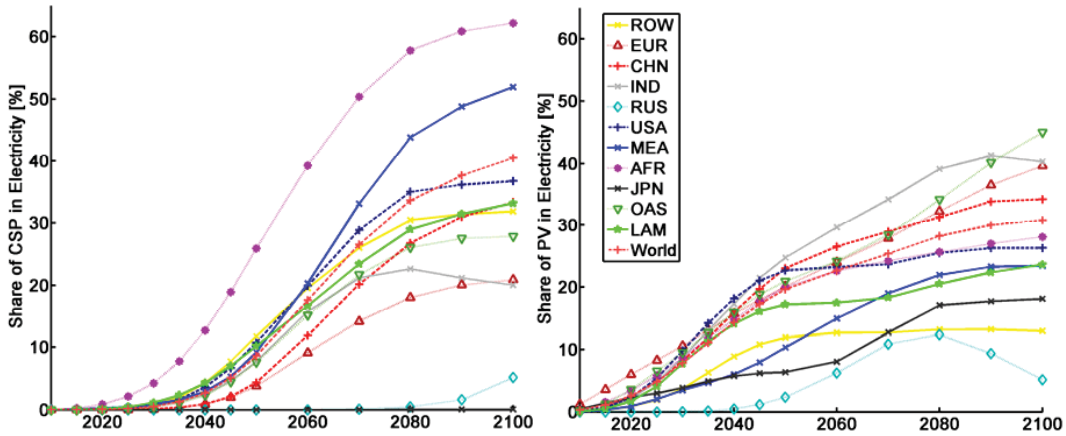
The technology exclusion scenarios have quite strong impacts on electricity prices, as was shown in Section 6.2 in the main paper. In SI Figure 1, we also show the electricity mixes in 2100. One can clearly see that gas, nuclear and wind use are expanded when both PV and CSP are excluded, but their LCOE and thus the electricity prices increase strongly so that the energy system reduces its electricity demand to less than half of the value in the default POL scenario.



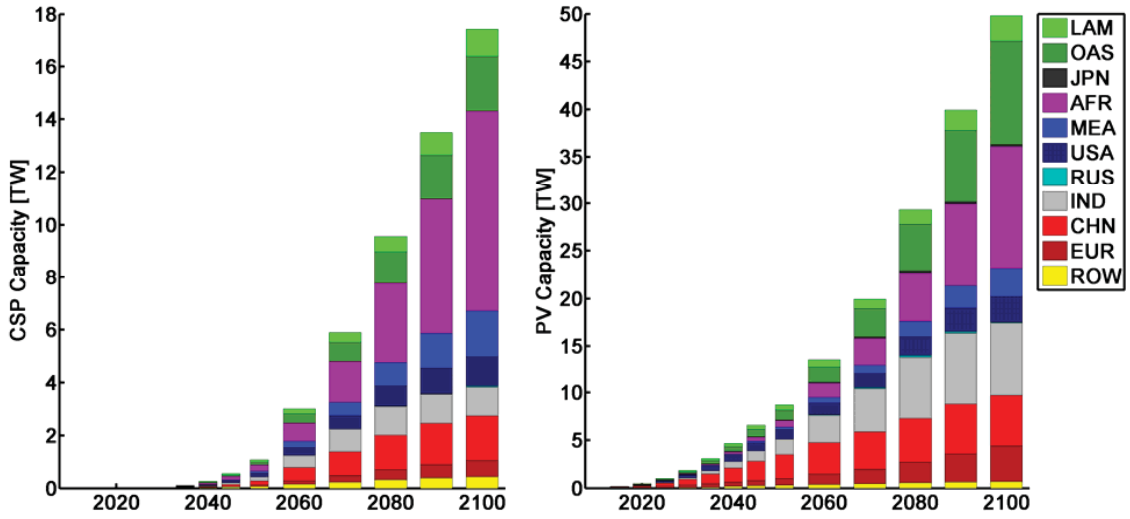
SI Figure 1: Electricity production in 2100 in the technology exclusion scenarios

SI 6: Regional distribution of solar power use

In SI Figure 2, we show the regional shares of PV and CSP in total electricity production. Some regions like sub-Saharan Africa and the Middle East strongly favor CSP in the long term, while other regions like Southeast Asia, India or Europe, which have on average a lower direct : indirect light ratio due to cloud cover, favor PV. The regional distribution of the installed capacities can be seen in SI Figure 3.



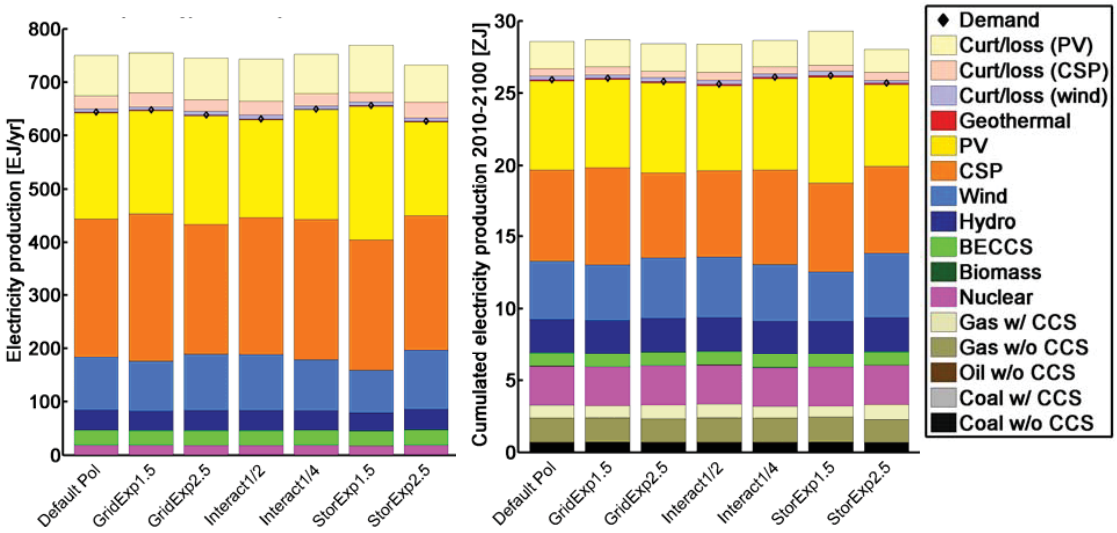
SI Figure 2: Time evolution of regional shares of CSP (left) and PV (right) in total electricity production in the POL climate mitigation scenario.



SI Figure 3: Regional distribution of installed CSP capacities (left) and PV capacities (right).

SI 7: Sensitivity of results to changes in the functional form of the storage and grid requirements

As discussed in Section 3.4 in the main paper, our storage and grid requirements represent strong simplifications compared to reality. Furthermore, bottom-up studies have not yet determined if specific integration costs increase more or less than linearly. We therefore performed a simple test of the robustness of our results with respect to the functional form of these requirements by varying the exponent a of the bracket in Equations 2-4 for the storage requirements and the exponent b of the bracket in Equation 5 for grid requirements from the default value of 1 to either 0.5 (resulting in a faster increase of integration costs at low shares, and lower integration costs at high shares) or 1.5 (a slower increase of integration costs at low shares, and higher integration costs at high shares). To stay comparable to the literature, we rescaled the SMSC/SMC/SMG values so that the marginal integration costs at 40% VRE share were the same across all runs. Furthermore, we also varied the interaction parameter between PV and CSP, from the default value of 1/3 to either ½ (a stronger correlation between PV and CSP, thus a stronger reciprocal increase of integration challenges) or ¼ (a weaker correlation between PV and CSP, thus a weaker reciprocal increase of integration challenges). As can be seen in SI Figure 4, all variations have only comparatively small effects on the electricity production, with the largest effect observable in the run where storage requirements increase less than linearly, leading to much higher PV use.



SI Figure 4: Influence of variations of the functional form of storage and grid requirements on the electricity mix in 2100 (left) and the cumulated electricity production (right).

Bibliography

[1] IHS CERA, "IHS CERA Power Capital Costs Index (PCCI)," 2013. [Online]. Available: http://ihsindexes.com/pcci-graph.htm. [Accessed: 22-Sep-2013].
[2] J. K. Kaldellis and D. Zafirakis, "Optimum energy storage techniques for the improvement of renewable energy sources-based electricity generation economic efficiency," *Energy*, vol. 32, no. 12, pp. 2295–2305, Dec. 2007.
[3] D. Steward, G. Saur, M. Penev, and T. Ramsden, "Lifecycle cost analysis of hydrogen versus other technologies for electrical energy storage," National Renewable Energy Laboratory, Golden (CO)(2009 Nov), Report No.: NREL/TP56046719, 2009.
[4] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, and Y. Ding, "Progress in electrical energy storage system: A critical review," *Prog. Nat. Sci.*, vol. 19, no. 3, pp. 291–312, Mar. 2009.
[5] C. K. Ekman and S. H. Jensen, "Prospects for large scale electricity storage in Denmark," *Energy Convers. Manag.*, vol. 51, no. 6, pp. 1140–1147, Jun. 2010.
[6] K. T. Cho, P. Albertus, V. Battaglia, A. Kojic, V. Srinivasan, and A. Z. Weber, "Optimization and Analysis of High-Power Hydrogen/Bromine-Flow Batteries for Grid-Scale Energy Storage," *Energy Technol.*, vol. 1, no. 10, pp. 596–608, Oct. 2013.
[7] M. Baumann, B. Zimmermann, H. Dura, B. Simon, and M. Weil, "A comparative probabilistic economic analysis of selected stationary battery systems for grid applications," in *Clean Electrical Power (ICCEP), 2013 International Conference on*, 2013, pp. 87–92.
[8] P. Alotto, M. Guarnieri, and F. Moro, "Redox flow batteries for the storage of renewable energy: A review," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 325–335, Jan. 2014.
[9] V. Viswanathan, A. Crawford, D. Stephenson, S. Kim, W. Wang, B. Li, G. Coffey, E. Thomsen, G. Graff, P. Balducci, M. Kintner-Meyer, and V. Sprenkle, "Cost and performance model for redox flow batteries," *J. Power Sources*, vol. 247, pp. 1040–1051, Feb. 2014.
[10] J. E. Mason and K. Zweibel, "Baseline model of a centralized pv electrolytic hydrogen system," *Int. J. Hydrog. Energy*, vol. 32, no. 14, pp. 2743–2763, Sep. 2007.
[11] M. N. Manage, D. Hodgson, N. Milligan, S. J. R. Simons, and D. J. L. Brett, "A techno-economic appraisal of hydrogen generation and the case for solid oxide electrolyser cells," *Int. J. Hydrog. Energy*, vol. 36, no. 10, pp. 5782–5796, May 2011.
[12] G. Fuchs, B. Lunz, M. Leuthold, and D. U. Sauer, "Technology Overview on Electricity Storage," 2012.
[13] P. Sullivan, V. Krey, and K. Riahi, "Impacts of considering electric sector variability and reliability in the MESSAGE model," *Energy Strategy Rev.*, vol. 1, no. 3, pp. 157–163, Mar. 2013.
[14] M. P. Bahrman and B. K. Johnson, "The ABCs of HVDC transmission technologies," *IEEE Power Energy Mag.*, vol. 5, no. 2, pp. 32–44, 2007.
[15] NASA, "Surface Radiation Budget Release 3.0.," National Aeronautics and Space Agency, Atmospheric Science Data Center, 2012.
[16] D. Stetter, "Enhancement of the REMix energy system model: Global renewable energy potentials, optimized power plant siting and scenario validation," University of Stuttgart, 2013.
[17] F. Trieb, C. Schillings, T. Pregger, and M. O'Sullivan, "Solar electricity imports from the Middle East and North Africa to Europe," *Energy Policy*, vol. 42, pp. 341–353, 2012.
[18] E. Bartholomé and A. S. Belward, "GLC2000: a new approach to global land cover mapping from Earth observation data," *Int. J. Remote Sens.*, vol. 26, no. 9, pp. 1959–1977, 2005.

[19] NEDO, “Solar Photovoltaic Generation Roadmap toward 2030 (PV2030),” New Energy and Industrial Technology Development Organization, Japan, 2004.
[20] Mizuho Information & Research Institute, “Mizuho Information & Research Institute,” 2013. [Online]. Available: http://www.mizuho-ir.co.jp/publication/contribution/2012/solarenergy0131_03.html. [Accessed: 01-Dec-2013].

Chapter 5

Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models*

Robert C. Pietzcker
Thomas Longden
Wenying Chen
Sha Fu
Elmar Kriegler
Page Kyle
Gunnar Luderer

*published in *Energy* as Pietzcker, R.C., Longden, T., Chen, W., Fu, S., Kriegler, E., Kyle, P., Luderer, G., (2014) "Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models". Energy 64, 95–108
dx.doi.org/10.1016/j.energy.2013.08.059

Energy 64 (2014) 95–108

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Long-term transport energy demand and climate policy: Alternative visions on transport decarbonization in energy-economy models

Robert C. Pietzcker [a, *], Thomas Longden [b], Wenying Chen [c], Sha Fu [d], Elmar Kriegler [a], Page Kyle [e], Gunnar Luderer [a]

[a] Potsdam Institute for Climate Impact Research, P.O. Box 60 12 03, D-14412 Potsdam, Germany
[b] Fondazione Eni Enrico Mattei and Centro Euro-Mediterraneo sui Cambiamenti Climatici, Corso Magenta 63, 20123 Milano, Lombardy, Italy
[c] Institute of Energy, Environment and Economy, Tsinghua University, Beijing 100084, China
[d] National Center for Climate Change Strategy and International Cooperation (NCSC), Beijing 100038, China
[e] Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, MD 20740, United States

ARTICLE INFO

Article history:
Received 18 January 2013
Received in revised form
23 August 2013
Accepted 30 August 2013
Available online 15 December 2013

Keywords:
Transportation scenarios
CO_2 (Carbon dioxide) emission mitigation
Hydrogen
Energy-economy modeling
BEVs (Battery electric vehicles)
Mobility demand reduction

ABSTRACT

Decarbonizing transport will be necessary to limit global warming below 2 °C. Due to persistent reliance on fossil fuels, it is posited that transport is more difficult to decarbonize than other sectors. To test this hypothesis, we compare long-term transport energy demand and emission projections for China, USA and the world from five large-scale energy-economy models. We diagnose the model's characteristics by subjecting them to three climate policies. We systematically analyze mitigation levers along the chain of causality from mobility to emissions, finding that some models lack relevant mitigation options. We partially confirm that transport is less reactive to a given carbon tax than the non-transport sectors: in the first half of the century, transport mitigation is delayed by 10–30 years compared to non-transport mitigation. At high carbon prices towards the end of the century, however, the three global models achieve deep transport emission reductions by >90% through the use of advanced vehicle technologies and low-carbon primary energy; especially biomass with CCS (carbon capture and sequestration) plays a crucial role. The extent to which earlier mitigation is possible strongly depends on implemented technologies and model structure. Compared to the global models, the two partial-equilibrium models are less flexible in their reaction to climate policies.

© 2013 Elsevier Ltd. All rights reserved.

1. Introduction

To limit global warming to less than 2 °C above pre-industrial temperatures, greenhouse gas emissions have to be strongly reduced in the near term with long-term emissions close to or below zero [1]. Transport contributed 22% to global CO_2 emissions in 2010 [2], and transport CO_2 emissions are projected to double by 2050, reaching 14–18 Gt CO_2 (IEA 2009). Decarbonizing the transport sector is thus a fundamental challenge that needs to be tackled to limit global warming. The research community has consistently posited the hypothesis that the transport sector tends to react less and later to mitigation policies than other sectors, and that the transport sector is quite difficult to decarbonize due to a reliance on fossil fuels and persistent demand [3–7]. This study sets out to test this hypothesis and advance the understanding of possible decarbonization pathways in the transport sector through the use of large-scale energy-economy models with embedded transportation modules. The study also has a diagnostic focus, as it presents and compares the results from transport modules of several energy-economy models that are and have been used for research and policy advice. In doing so, we discuss the strengths and weaknesses of the different models.

Accurate short-term projections of transport for a city or region is best performed with detailed bottom-up models that include spatially explicit infrastructure modeling. In contrast, the analysis of long-term transformations to achieve climate targets requires large-scale energy-economy models that aggregate the detailed mitigation actions into general trends and that are able to represent the interactions between different sectors and regions via resource prices, capital flows and technology diffusion.

Decarbonization options for the transport sector exist on many different levels: Total demand for mobility can be reduced through increased travel costs, improved (urban) infrastructure, changes in consumer preferences and socio-cultural norms. Modal shift from travel modes with high carbon intensity such as aviation or private vehicles to ones with lower carbon intensity such as buses, trains or

* Corresponding author. Tel.: +49 331 288 2404.
E-mail address: pietzcker@pik-potsdam.de (R.C. Pietzcker).

0360-5442/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.energy.2013.08.059

ships will reduce GHG (greenhouse gas) emissions. Within one travel mode, energy demand and thus emissions can be reduced through more efficient vehicles (either through technological change or smaller and lighter vehicles), as well as increased load factors. Switching to advanced vehicles like plug-in hybrids, battery electric vehicles or fuel cell vehicles not only increases efficiency, but can also open up new paths to low-carbon primary energies like renewable energies or nuclear. Finally, the Fischer–Tropsch process allows the production of liquid fuels from biomass, coal or natural gas, both with or without CCS (carbon capture and sequestration) [8–10].

Decarbonization options within the electricity sector have been focused on extensively within the modeling literature and are relatively well understood. Furthermore, the first comprehensive mitigation policy targeting the electricity sector has been in place for more than five years, as reflected in the establishment of the EU ETS (EU Emissions Trading System). In contrast, the systematic analysis of transport sector decarbonization is at a much earlier stage. Until the 2000s, large-scale transportation studies focused mostly on projections of global mobility and the implications for energy demand and emissions, while measures to reduce emissions were not analyzed [11,12].

In the last decade, some progress in the analysis of transport sector decarbonization has been achieved. There have been a number of transport studies with a strong mitigation focus at the level of nations or regions [13–17], but only a few utilize an integrated global approach. When studies have analyzed global mitigation, they often limit the analysis to the LDV (light duty vehicle) sector and its different technology options for mitigation [18–25]. Other studies model the full transport sector, but do not include direct feedbacks between the rest of the energy system and the transport sector [26]. This allows the use of a very detailed transport model, but prevents all interactions between the different sectors. As the transport sector is a main driver for the demand for liquid fuels, ignoring the feedback on oil and biomass prices is a strong limitation for such a study. Azar et al. developed a linear partial-equilibrium energy system model including a detailed transport sector at the global [27] and regional level [28]. In a comparison study they also tried to reconcile contrasting results from two different transport models about the use of biomass for transport [29].

Besides price signals on CO_2, various other policies can have a substantial influence on mobility demands, and thus CO_2 emission. Cuenot et al. use the IEA's mobility model to develop a passenger transport scenario in which a variety of measures including strong policy action result in strong modal shifts towards less energy-intensive modes, leading to a 20% decrease in CO_2 emissions compared to their reference scenario [30].

This study presents the analysis of transport decarbonization that was carried out within the Climate Policy Outreach project. It brings together a range of large-scale energy-economy models with dedicated transport modules, namely:

- CHN-TIMES, from Tsinghua University, based on the China MARKAL model [31–33]
- GCAM, from Pacific Northwest National Laboratory [22,34]
- PECE, from Renmin University of China [35,36]
- REMIND 1.4, from Potsdam Institute for Climate Impact Research [6,7,37,38]
- WITCH-T, a modification of the WITCH (World Induced Technical Change Hybrid) model with a transport module added, from Fondazione Eni Enrico Mattei [39–41]

Utilizing a variety of models means that we can diagnose how different model structures influence the projections for transport energy demand and the emission reductions achievable. We apply a consistent set of climate policies with varying stringency to all the models by implementing three different carbon tax regimes. These harmonized climate policies allow for a detailed comparison of the flexibility of different models and the analysis of robust of mitigations options.

We contribute to the existing literature by i) comparing transport mitigation efforts across five energy-economy models that were all subject to the same climate policies, ii) bridging the scales by discussing both world and country level results, with China and the US taken as examples for emerging and developed countries, iii) systematically analyzing the mitigation levers along the chain of causality from mobility to primary energy, and iv) discussing the structural differences between mitigation in the transport sector and the non-transport sectors.

The paper is structured as follows: Section 2 describes the key traits of the participating models and the climate policy scenarios applied to them, as well as presenting the chain of causality on which the later analysis is based. Section 3 presents the general results from the model runs: 3.1 reviews each of the model's final energy demand in the reference scenarios to gain an understanding of the different projections of the world without climate policy. Section 3.2 presents the emissions in the different policy scenarios. Section 4 develops the analysis: Section 4.1 focuses on the climate mitigation options that occur within the transport sector under the various mitigation policies. Section 4.2 contrasts the transport sector with the non-transport sectors. Section 5 concludes the paper with an overview of the robust characteristics of transport decarbonization emerging across the models and a discussion of caveats and future research needed.

2. Methodology

This study is based on the comparison and analysis of modeling results from large-scale energy-economy models. To be able to interpret the results and develop an understanding for the dynamics behind these results, one has to understand the basic model properties, which are discussed in this section.

2.1. Model description

All participating models include a detailed energy system that converts primary energy inputs into distinct final energies that are demanded for the production of energy services such as mobility.

Mobility demand and travel choices are influenced by a number of interdependent drivers, including income, fuel and technology costs, motorization rate, infrastructure, congestion, transport policies (such as tolls or licensing), and life style. Although it is very challenging to project exact travel numbers on a detailed local or national level, several stylized facts about transport have been identified that come to bear at large scales and help to make aggregated projections of transportation. A stylized fact implemented by Yacov Zahavi in his "Unified Mechanism of Travel" model [42] and later discussed and refined by others [12,43], states that across a wide variety of regions and cultures it is possible to find regularities about the amount of time (about 1.1 h per day) and the share of personal income (about 10–15% percent at high motorization rates) that people spend on mobility. These stylized facts allow for a linkage of broad mobility demands to personal income, as well as cost of travel. In addition, the observation of a travel time budget in combination with finite travel speeds leads to a saturation effect of total travel demand [12]. The limited speed of LDVs (which is even further reduced through congestion) is one factor that leads to saturation of demand for private motorized travel.

The models take into account these drivers for the parameterization of their mobility demand function either implicitly or

Table 1
Overview of basic model properties.

	Objective function	Dynamics	Runs until	Regional Coverage	Mobility demands	Technology choice based on	Endogenous learning
CHN-TIMES	Minimize energy system costs	Recursive-dynamic	2050	China	Exogenous projection	Linear least-cost	No
GCAM	Minimize social costs	Recursive-dynamic	2100	Global	Endogenous with fixed price and income elasticity	Logit-shares based on cost	No
PECE	Minimize energy system costs	Recursive-dynamic	2050	China	Exogenous projection	Linear least-cost	Yes
REMIND	Maximize welfare	Inter-temporal optimization	2100	Global	Endogenous CES production function	Intertemporal cost minimization	Yes
WITCH-T	Maximize welfare	Inter-temporal	2100	Global	Exogenous projection (all other FE: endog. CES function)	Transport: linear least-cost. Other: intertemp. cost minimization	Yes

explicitly. The specifics of the transport modeling that are important for the further analysis are briefly presented in the following paragraphs, including references for more explicit documentation and previous use of the models.

2.1.1. China TIMES (CHN-T)

For the CHN-TIMES model, mobility demands for all transport modes (see Table 2) are projected exogenously based on regressions on GDP (Gross Domestic Product)/cap (for passenger transport) or GDP (for freight transport), as well as assumptions about vehicle ownership (with saturation level considered) and expected modal shift. To fulfill the projected price-independent mobility demands, the model then chooses investments into different vehicle technologies according to investment-time fuel prices and technology investment costs. Investment costs for advanced light duty vehicles, such as hybrids, BEV (battery-electric vehicles) or FCV (fuel cell vehicles), decrease exogenously over time. Modal shift is not endogenously modeled. The model has a scenario-independent lower limit of 2% annual growth rate for BEV, while not limits were set for FCV.

2.1.2. GCAM

In summary, the transportation services modeled include passenger transport, freight transport, and international shipping, with the demand for each service driven by per-capita GDP and population. Each type of service demand is met by a range of competing modes. Changes in modal shares in future periods depend on the relative costs of the different options, modeled using a logit choice formulation. Costs in the passenger sector include time value of transportation, which tends to drive a shift towards faster modes of transport (light duty vehicles, aviation) as incomes increase. Many of the modes (including light-duty vehicles) include competition between different vehicle types, which also uses a logit choice mechanism that is calibrated to base-year shares. For new or emerging technologies (e.g. electric or hydrogen vehicles), costs also consider infrastructural constraints, non-economic consumer preferences, and as such are especially high in the near-term future time periods. No upper limits of BEV or FCV use are implemented.

2.1.3. PECE

For the PECE model, mobility demands for all transport modes are exogenously projected based on regressions on GDP/cap and vehicle ownership (with saturation level considered) as well as expected modal shift. To fulfill these price-independent mobility demands, the model chooses investments into different vehicle technologies according to investment-time fuel prices and technology costs. Investment costs for advanced vehicles (hybrids, BEV, FCV) decrease endogenously through learning-by-doing. Modal shift is not endogenously modeled. The model has a scenario-independent upper limit of 25% to BEV usage.

2.1.4. REMIND

In REMIND 1.4, mobility demands are endogenously determined through a nested CES (Constant Elasticity of Substitution) production function, with CES efficiency parameters chosen such that the Reference scenario follows a region-specific exogenous projection based on GDP and population. In the LDV sector, the model can choose between different vehicle technologies based on a minimization of the intertemporal costs (fuel prices at each time step and investment costs). Investment costs for advanced vehicles

Table 2
Overview of transportation sector representation in the different models.

	Transport Sector							
	Passenger				Freight			
	LDV	Rail	Bus	Aviation	Truck	Rail	Aviation	Navigation
CHN-T	Y	y	y	y	y	y	y	y
GCAM	Y	y	y	y	y	y	y	y
PECE	Y	y	y	y	y	y	y	y
REMIND	Y	y	aggregated		aggregated			
WITCH-T	Y	y	n	n	y	y	n	n

light green ("y"): This mode is individually represented in the transport module.olive green ("aggregated"): This transport mode is represented not individually, but clustered together with other transport modes.red ("n"): This transport mode is not represented in the transport module.

Table 3
Mapping of energy carriers to transport sectors.

		CHN-T	GCAM	PECE	REMIND	WITCH-T
LDVs use	Liquids	y	y	y	y	y
	Liquids (efficient)	y	n	y	n	y
	Gas	y	y	y	n	n
	Power	y	y	y	y	y
	H2	y	y	y	y	n
Fuels used for freight	Liquids	y	y	y	y	y
	Gas	y	n	n	n	y
	Power	y	n	y	n	y
	H2	n	n	n	n	n
Fuels used for aviation	Liquids	y	y	y	y	N/A
	Gas	n	n	n	n	
	Power	n	n	n	n	
	H2	n	n	n	n	

light green ("y"): This energy carrier can be used for the stated transport mode.red ("n"): This energy carrier cannot be used for the stated transport mode.white ("N/A"): This transport mode is not represented in the transport module, thus it makes no sense to ask if a certain energy carrier can be used for the stated transport mode.

(BEV, FCV) are endogenously reduced through learning-by-doing. Modal shift between LDVs and the other transport sectors is possible via a CES substitution elasticity of 1.5. The model has scenario-independent upper limits to BEV/FCV usage: at all times, the maximum share of BEV is 60%, of FCV is 80%.

2.1.5. WITCH-T

For the WITCH-T model, mobility demand for all transport modes is exogenously projected based on regional GDP/cap and vehicle ownership per capita. To determine the price dependent final energy demands arising from the mobility demand, the model chooses investments in different vehicle technologies according to lifecycle costs, consisting of vehicle investment costs plus O&M and fuel expenditure for each time step. Investment costs for advanced vehicles (hybrids, BEV) decrease endogenously through learning-by-searching. Modal shift is not endogenously modeled. The model constrains BEV usage through cost alone.

Table 2 presents the detail at which the transport sector is represented in the models, breaking down the sector by Passenger and Freight, as well as the sub-categories LDVs, Truck, Rail, Bus, Aviation and Navigation. Table 3 focuses on the transport fuels included in the model and adds to the description contained within Table 2 by reviewing the coverage of these fuels across models and type of vehicle. As the dominant energy carrier type for the transport sector in all models is liquid fuels, Table 4 focuses on which primary energies are used for the production of liquid fuels in the different models. Extraction/production costs for these primary energy resources (crude oil, coal, gas, biomass) rise over time and deployment, with some models representing broad world markets based on detailed resource extraction cost curves (GCAM, REMIND, WITCH), while others assume independent production cost curves for each region. The importance of the fuel coverage within the models will become evident upon reviewing the decarbonization scenarios contained in section three.

2.1.6. Vehicle ownership

One crucial parameter influencing modal shares for passenger transport is the motorization rate, usually measured as the number of LDVs per thousand people. The motorization rate is both a driver and a consequence of transport choices in that it is influenced by per-capita income, population density inside cities, infrastructure, availability of other transport modes, life styles, and geographic

Table 4
Primary Energy types usable for liquid transport fuels.

		CHN-T	GCAM	PECE	REMIND	WITCH-T
PE usable for liquid transport fuels	Crude Oil	y	y	y	y	y
	Biofuel	y	y	y	y	y
	Bio+CCS	n	y	y	y	n
	Coal	y	y	y	y	N
	Coal+CCS	y	y	y	y	N
	Gas	y	y	y	n	N

light green ("y"): This PE can be used for the production of liquid transport fuels.red ("n"): This PE cannot be used for the production of liquid transport fuels.

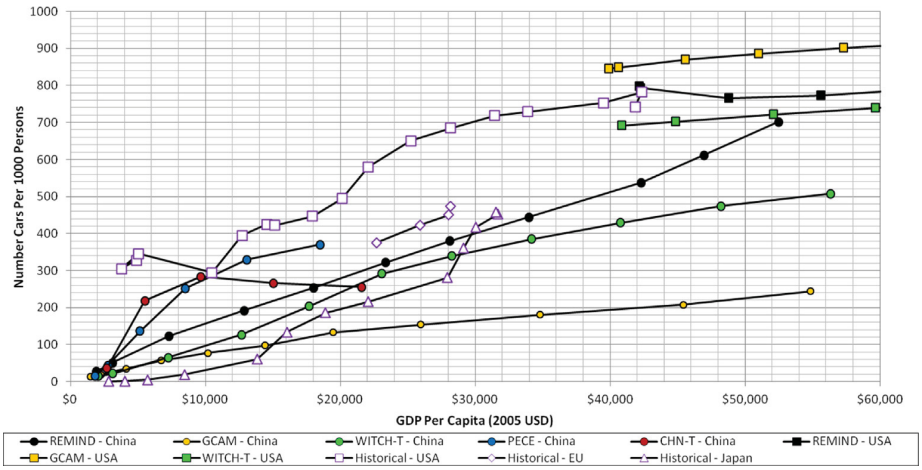


Fig. 1. Projected motorization rates for China and the US from 2010 to 2100 in 10 year time steps, as well as historic values for US (1930–2010), EU (1990–2010) and Japan (1950–2010). Numbers based on Refs. [18,45–50].

parameters, while at the same time, motorization also influences travel choices, transport policies and infrastructure development. Historic motorization rates at certain per-capita income levels have varied by a factor of three in different regions (see Fig. 1), so the projection of motorization in a certain country will depend substantially on how one expects the life style and infrastructure of this region to develop.

Fig. 1 shows the range of values projected by the different models. All of the models forecast that China will have lower motorization levels than the US had historically, although the models diverge on whether it will move closer to the EU's or Japan's path. As China's cities have grown substantially over the last decades without being planned for large numbers of LDVs, it seems plausible that China will stay at much lower motorization rates than those within the US, where suburban structures co-evolved with the spread of automobiles. For a comparison, Hao et al [44] develop a detailed stratified rural/urban model to project Chinese vehicle numbers out to 2050 and arrive at 400 cars per 1000 persons at a per-capita income of ~35,000 US$ which coincides closely to estimates of the WITCH-T and REMIND models.

PECE and CHN-TIMES see the fastest rise over the next two decades with up to 300 cars per capita at per-capita incomes below $10,000 (a six-fold increase over 2010), but then show notable saturation effects, with CHN-TIMES projecting an actual decline in motorization rates. The global models see a slower, more linear growth: WITCH-T and REMIND project that China reaches a level of vehicle ownership similar to Japan and the EU in the late 1990s, while GCAM projects much lower motorization rates that remain below the values seen in Japan for similar per capita incomes.

2.2. Policy scenarios

To compare the reaction of the different models to climate policy, three global economy-wide carbon tax paths starting in 2015 and rising by 5% per year were imposed on the models (Table 5), thus following the design of the Asian Modeling Exercise [51] scenarios. Using globally uniform taxes instead of CO_2 concentration targets allows for a direct comparison between global and national models, while the flexibility of the models can be explored with the three different tax levels.

Table 5
Description of Scenarios, all values in US$(2005)/t CO_2.

Brief description	Policy scenario name	Tax level 2020	Tax level 2050	Tax level 2100
No carbon policy	REF	0	0	0
Global economy-wide carbon tax in all sectors	TAX10	10	43	496
	TAX30	30	130	1487
	TAX50	50	216	2478

2.3. Following the chain of causality

To better understand and interpret the behaviors of the transport sector in the different models, it is useful to follow the "chain of causality" implemented in the models (refer to Fig. 2). Each model includes a demand for energy services (for the transport sector: mobility), measured in passenger km for passenger transport and ton km for freight transport. This mobility demand can either be exogenously prescribed or can result from a simple economical demand model (refer to Table 1 for an overview of which model uses what approach), and it can be specified for each individual transport mode or aggregated across several modes. The mobility demand is translated into FE (final energy) demand by different vehicles, with vehicle types determining the energy carrier type (liquid, gas, electricity, hydrogen) and amount of FE demanded (efficient vs. less efficient vehicles, refer to Table 3). These FE demands are then fulfilled by the energy systems of the models, with different PE (primary energy) types usable for different FE types. The type of PE used determines the total well-to-wheel CO_2 emissions for the FE provision, with some conversion routes allowing the use of CCS to decrease emissions from this PE (refer to Table 4). Along each step, mitigation options exist that influence the amount and type of the drivers; as displayed in Fig. 2. Some models implement more and some less of these mitigation options.

When discussing CO_2 emissions, this study always uses well-to-wheel emissions, thus including end-of-pipe emissions (e.g., from burning gasoline in a car engine) as well as well as the emissions from the energy transformation process (e.g., emissions from a coal power plant for the production of electricity used in an electric car).

The data and figures used in the following sections tend to be split between the transport sector and all other sectors (aggregated under the name "non-transport sectors") as this facilitates the analysis of fundamental differences between mitigation in the transport sector compared to the non-transport sectors.

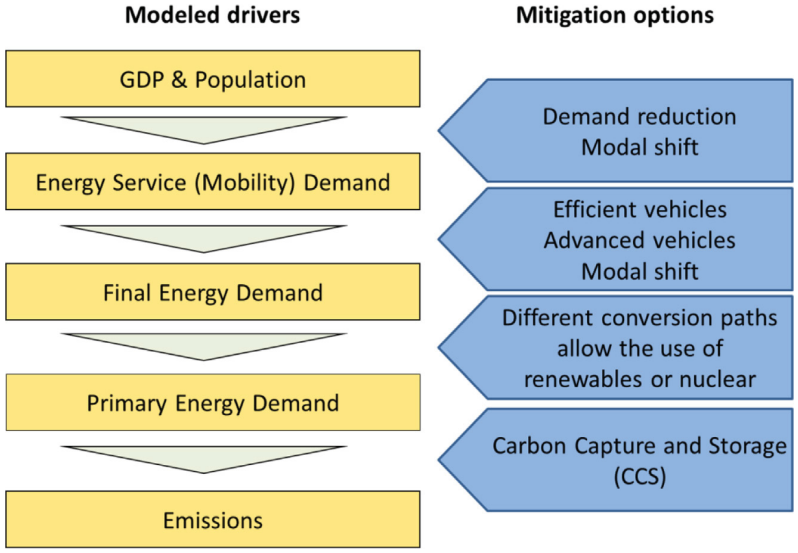


Fig. 2. Chain of causality in the transport sector.

3. General scenario results

3.1. Transport final energy demand in the reference scenario

This section reviews each of the model's reference scenarios to compare the different projections of the state of the world without climate policy. In doing so, it also reviews the different model attributes and formulations that have contributed to establishing these results. Fig. 3 shows the reference final energy projections for the overall economy, the transport sector, and light duty vehicles.

With respect to the final energy use in the overall economy, differences across models occur based on different base years,

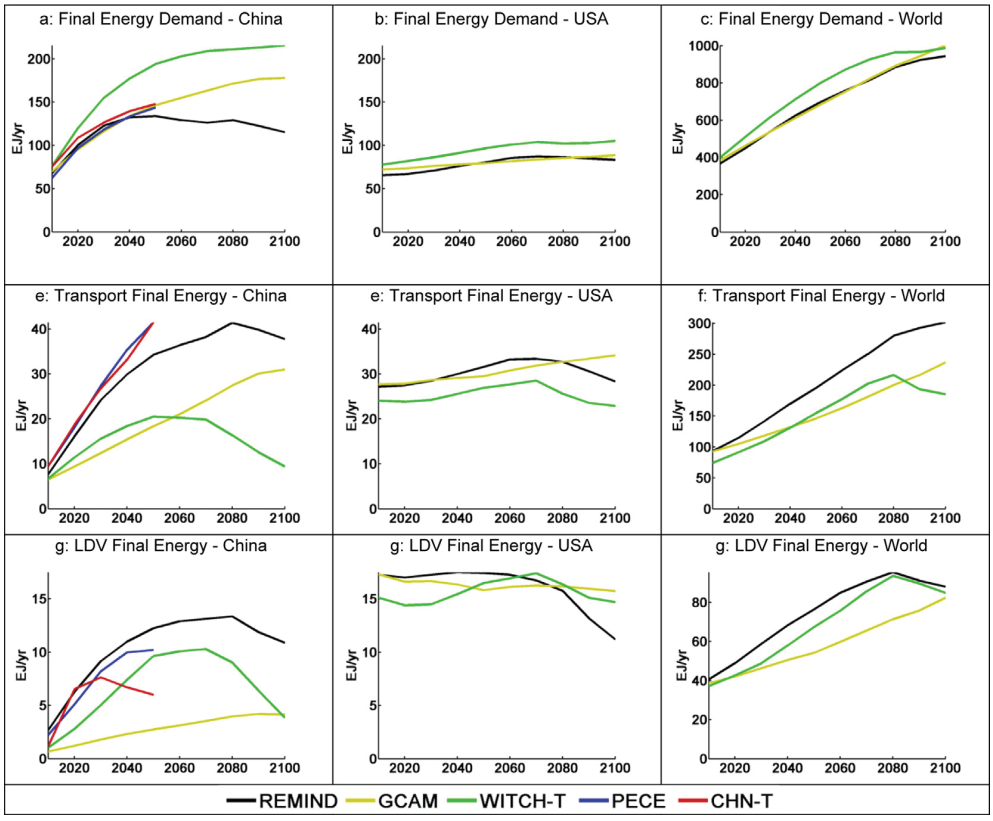


Fig. 3. Final energy demand projections in the reference scenario. a–c: Whole economy. d–f: Transport. g–i: Light duty vehicle sector.

differing national data used for calibration, and differences in model assumptions about population growth, economic growth and autonomous energy intensity reductions.

All models project a strong increase of final energy use in China and for the whole world, while seeing only marginal growth in the US (Fig. 3a–c). For China, the models see strong growth in the first half of the century, from 62 to 75 EJ/yr in 2010 to 134–194 EJ/yr in 2050. After this doubling/tripling, the final energy increase slows (WITCH-T, GCAM) or even turns negative (REMIND), leading to a large range of 2100 values from 115 to 215 EJ/yr. For globally aggregated final energy demand, the three global models are much more similar in their projections, showing an almost linear increase from 368 to 401 EJ/yr in 2010 to 943–1000 EJ/yr in 2100.

For China, final energy demand from the transportation sector shows an even larger variation (Fig. 3d–f). Both national models show an almost linear increase, leading to a four-fold increase within 40 years, from 9 EJ/yr in 2010 to 41 EJ/yr in 2050. GCAM also shows an almost linear increase, but with a much lower slope, reaching only 31 EJ/yr in 2100. Both REMIND and WITCH-T express a different behavior: after an initial increase, both models peak and decrease due to fuel switching towards electricity. REMIND projects a strong initial growth, leading to a 2100 value of 38 EJ/yr. WITCH-T already starts with a low growth, so that the peak-and-decline results in a very low demand of 9 EJ/yr in 2100. Note that the WITCH-T transport final energy demands reviewed in Fig. 3 and onwards do not include energy for air travel or international navigation – for modeling reasons, these energy demands remain in an aggregated non-electricity sector.

For the US and the world aggregate, the three global models produce more similar transport energy demands than for China. Still, they each display their characteristic pattern: GCAM sees a relatively linear increase, REMIND shows a faster increase with a slight decline in the last third of the century, and WITCH-T shows a strong decrease in the last decades. The strong decrease in WITCH-T can be traced back to the possibility of also electrifying freight transport, which is not included in the other global models. This

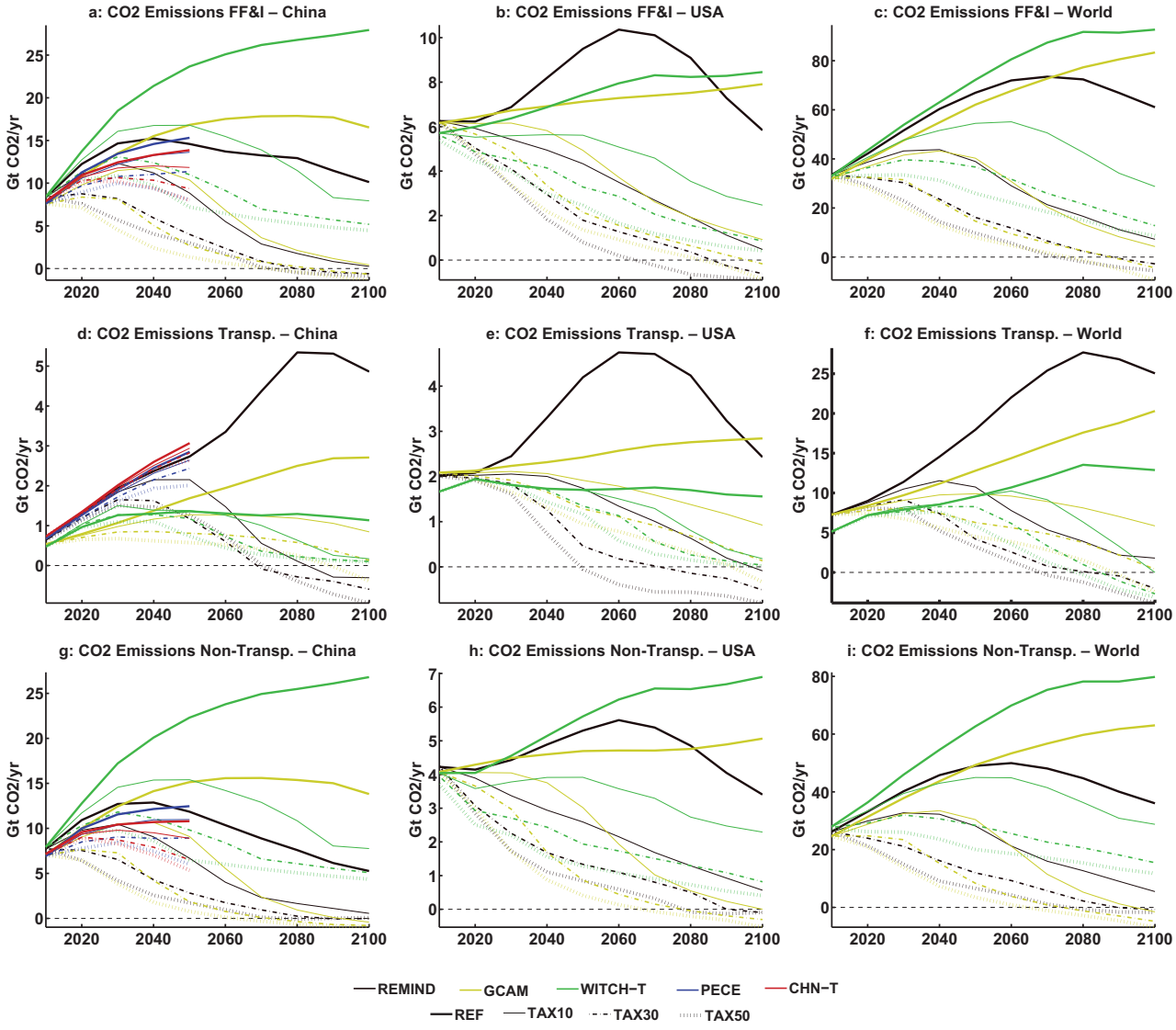


Fig. 4. Well-to-wheel CO_2 emissions across policy scenarios. a–c: Fossil fuel and industry. d–f: Transport sector. g–i: non-transport sectors.

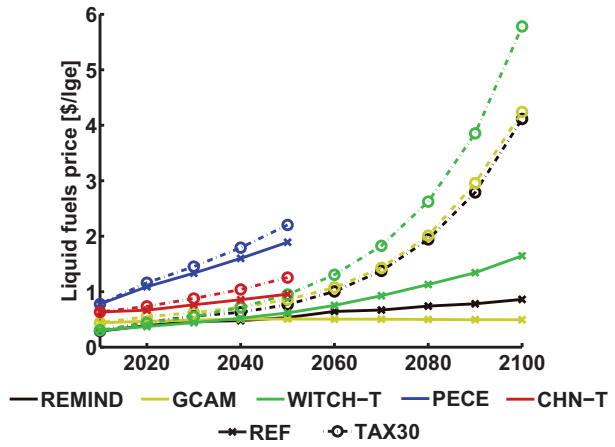


Fig. 5. Liquid fuels price at secondary energy level (including carbon taxes, excluding transport and distribution costs and other taxes) for Reference and Tax30 scenarios.

strong electrification of transport (not including air travel or international navigation) in WITCH-T and the partial electrification in REMIND already in the reference scenario is driven by the endogenous increase in oil prices – in WITCH-T, oil prices increase 5-fold until 2100, in REMIND 3-fold, while in GCAM they increase only by 50% compared to 2005.

Focusing on light duty vehicles, the models again show quite some differences for China. PECE, CHN-TIMES and REMIND show strong initial increases of LDV energy demand leading to a 4-fold increase from 2010 to 2030. CHN-TIMES then decreases LDV energy demand down to 6 EJ/yr in 2050, while PECE shows a leveling-off around 2050 at 10 EJ/yr, and REMIND increases until it shows the "electromobility kink" after 2080. GCAM follows a different storyline with a very slow linear increase of final energy demand for LDVs, reaching only 4 EJ/yr in 2100. WITCH-T sees an initially stronger increase halfway between GCAM and the other models, followed by a very strong downturn after 2070, so that it also reaches 4 EJ/yr in 2100 Again, the downturn within WITCH-T results from a leveling-off of passenger mobility demand combined with strong electrification of LDVs.

US and global values are much more similar between the models, with all models projecting a doubling of World LDV energy demand from 37 to 41 EJ/yr in 2010 to 82–88 EJ/yr in 2100. Again, WITCH-T and REMIND show a strong ramp-up of electric vehicles, leading to a noticeable reduction in energy demand at the end of the century.

3.2. Emissions

The observed growth in final energy demand in the reference scenario leads to a substantial growth in total CO_2 emissions from fossil fuels and industries, as can be seen in Fig. 4a–c. Although the results show major differences in the exact emission paths projected by the different models, many patterns are similar. In REF in all models, the strong short-term economic growth drives a substantial growth of emissions for China, reaching 14–24 Gt CO_2 in 2050 (2010: ~8 Gt CO_2). For the US, the emission projections rise much slower, leading to 2050 emissions of 7–9 Gt CO_2 (2010: ~6 Gt CO_2). For the second half of the century, emissions either stay close to their 2050 levels (GCAM, WITCH-T) or decrease substantially towards the end of the century (REMIND). This decarbonization in REMIND even in REF results from the combination of high emissions in the midst of the century due to strongly fossil-fueled growth (including substantial use of emission-intensive coal-to-liquid technologies) with a high long-term deployment of renewable electricity.

Under climate policy, all models show similar behavior in that the emission reductions achieved between TAX30 and TAX50 are much smaller than those achieved between REF and TAX10 or TAX10 and TAX30. Thus, the models become stiffer once a certain level of mitigation is reached, but the level at which the stiffness increases differs between the models. In most subsequent figures, only one climate policy scenario is shown to increase readability of plots.

REMIND and GCAM appear similar in as much as they project substantial decarbonization with emissions close to or even below zero at the end of the century even in the weakest climate policy scenario. WITCH-T projects a stronger increase in emissions in REF and also seems somewhat less flexible in the policy scenarios, leading to substantial residual emissions (close to 2005 emissions on world average) at the end of the century in the TAX10 scenario.

For China, CHN-TIMES projects the lowest FF&I emissions until 2050, but also the least emission reductions vs. REF in all policy scenarios. In strong policy scenarios, REMIND and WITCH-T project negative emissions in the transport sector, while GCAM achieves negative emissions in the non-transport sector. These negative emissions arise from the combination of CCS technology with (near carbon neutral) biomass, used for the production of power, liquid biofuels, biogas or hydrogen.

4. Analysis and discussion of mitigation pathways

4.1. Transport decarbonization

The results reveal that the models have very different visions of the routes towards transport decarbonization, as well as of the emission reductions achievable. To systematically analyze the mitigation pathways, we follow the chain of causality described in Section 2.2. We thus start with mobility demand, discuss the vehicle choices that translate the mobility demand into final energy demand, and then analyze the primary energies that are used to produce these final energies.

The models have regionally differentiated GDP and population growth assumptions, which lead to different transport mobility demand trends for the regions. When analyzing mitigation, however, the differences between models are much more pronounced than the differences between regions – thus, each model shows similar decarbonization patterns in most regions. For sake of brevity, we will thus limit the discussion of transport decarbonization patterns to China.

The main drivers of changes to the modeled transport system are fuel prices (incorporating the carbon price effect), which are displayed in Fig. 5. For comparability reasons, we show the price for liquid fuels in terms of secondary energy, which includes carbon taxes but excludes all other taxes, as well as the distribution costs to the final customer. Although dependence on liquid fuels is reduced in the Tax30 scenario, the share of liquids from crude oil in transport fuels stays above 25% in all of the models, so the marginal price of oil-based liquids remains a useful proxy for transport costs.

Fig. 5 shows the wide spread of fuel prices in the different models, as well as the strong long-term effect of carbon taxes on fuel prices. All the general equilibrium models show low fuel prices in the first half of the century, which can be traced back to the fact that they use extraction cost curves for oil based on detailed technological resource studies. As the fundamentals have not substantially changed over the last decade and the models do not include psychological factors like risk of unrest in the Middle East, these models have difficulties reproducing the tripling of oil prices after 2003. The partial-equilibrium models start at higher prices, and PECE also sees a doubling of prices from 2010 to 2050.

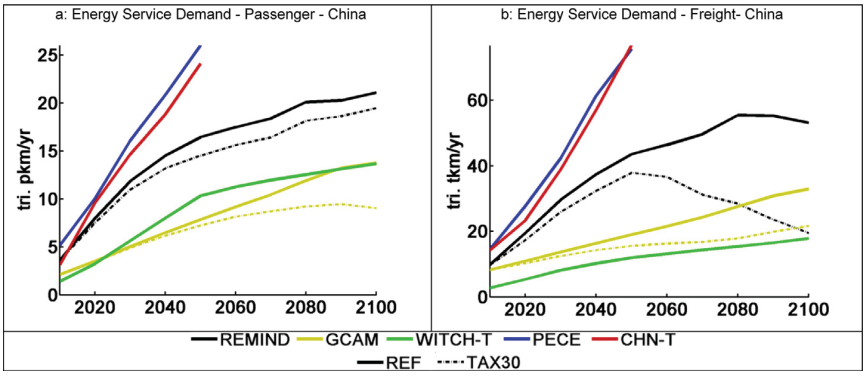


Fig. 6. Reaction of energy service demand to climate policy – REF and TAX30.

In the Tax30 scenario, the carbon content of crude oil increases the fuel price, which then drives mitigation action in the models. Until 2050 the carbon markup is smaller than the resource price, but the exponential increase of the carbon tax leads to very high carbon markups that are 2.5–7 times larger than the resource price at the end of the century.

The impact of the carbon policies on energy service demands can be seen in Fig. 6. Although carbon prices reach 130 \$/t CO_2 in 2050 (equivalent to 0.3 \$/liter of gasoline) and 1500 \$/t CO_2 (3.5 \$/l) in 2100 in TAX30, only GCAM and REMIND show any reaction of either freight or passenger demand to the carbon policy, while CHN-TIMES, PECE and WITCH-T implement mobility demands that are not influenced by changes in transport prices between the scenarios and thus stay the same under all climate policies. The fixed energy service demand makes these models less flexible in reacting to climate policy.

The final energies used to supply the transport energy service demands can be seen in Fig. 7. In the policy scenarios, all models reduce the total amount of final energy used for transport, either by deploying more efficient liquid-based vehicles, or by switching to other fuels which are more efficient (BEV, FCV).

Most striking is the strong reliance of all models on liquid fuels until 2050 – all models but WITCH-T keep the share of liquid fuels in transport final energy above 87% in every scenario. WITCH-T strongly increases the share of gaseous fuels in transport to up to 25% in REF, while in CHN-TIMES, PECE and GCAM, the share is 1–6% in all scenarios. The use of gas is driven by fuel costs and not emission reductions: both PECE and CHN-TIMES don't increase the gas use for transport in policy scenarios, and WITCH-T actually decreases the share as climate policy becomes more stringent. Electromobility is slow to enter the scene: Even in the strongest policy scenario, WITCH-T is the only model that supplies 25% of transport final energy in the form of electricity, while all other models stay below 10%. Hydrogen is even scarcer; no model goes beyond 3% of transport FE in 2050.

In 2100, however, the models react substantially to climate policy – WITCH-T increases electrification from REF to TAX50 from 51% to 76% (no hydrogen vehicles are included in WITCH-T), while REMIND and GCAM increase the combined share of electricity and hydrogen from less than 10% to about 50%. The strong electrification in WITCH-T is possible because the model a) includes electrification of freight, b) projects a higher oil price than the other global models, and c) does not include aviation and international navigation in the transport final energy demand.

Given that transport final energy demand decreases only in the range of 25–55% in the TAX30 scenario compared to REF, the strong long-term transport emission reductions of 60–110% seen in the global models (refer to Figs. 4d–f and 10a) must come from the decarbonization of the final energies used in the transport sector. This is demonstrated in Fig. 8, which plots the shares of transport final energy demand broken down by the primary energy from which they were produced. This allows tracing back the different

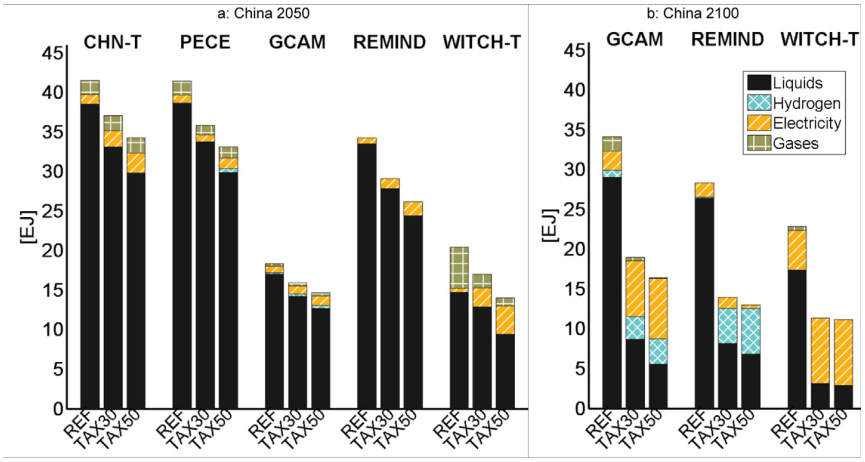


Fig. 7. Reaction of transport final energy demand to climate policy.

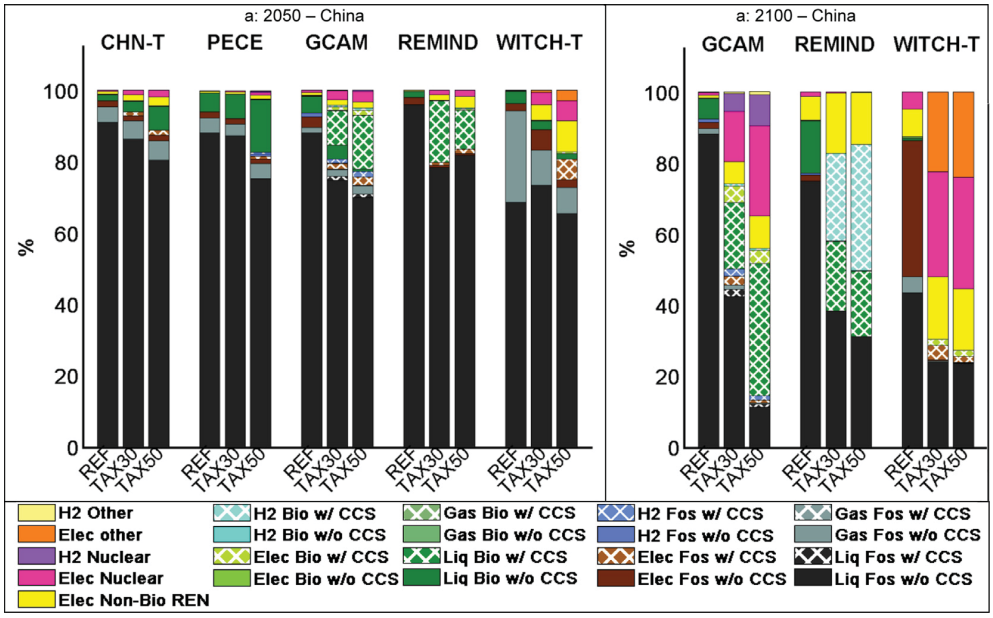


Fig. 8. Share of transport final energy broken down by primary energy type.

relative reduction levels achieved in the national and the global models to the changes in primary energy employed for transport.

In 2050, the main decarbonization action is the replacement of some crude oil by biomass as feedstock for liquid fuels (combined with CCS in GCAM and REMIND). When comparing the two national models, CHN-TIMES is more flexible in introducing advanced vehicle types, doubling the share of electricity in transport final energy from REF to TAX30, while PECE keeps the electricity share the same and invests more into more efficient vehicles, reducing final energy demand from transport by 14% compared to a reduction of 11% in CHN-TIMES. On the other hand, PECE is more flexible on the primary energy side: it substitutes crude oil with biomass in strong policy scenarios. In a TAX30 scenario, this leads to 2050 emission reductions of 14% relative to REF transport emissions, compared to 8% in CHN-TIMES.

In 2100, the use of electricity/hydrogen in combination with the high carbon prices in TAX30 leads to major changes: 20% (WITCH-T), 30% (GCAM) or 60% (REMIND) of the final energy used in transport are produced from renewables. REMIND relies mostly on biomass in combination with CCS (BECCS), producing both liquid fuels and hydrogen with net negative emissions, as well as non-biomass renewables to produce electricity. GCAM relies both on BECCS for liquid fuels as well as nuclear for hydrogen and electricity. The strong electrification in WITCH-T make nuclear, other low-emissions sources for electricity and non-biomass renewables the main primary energy inputs to transport.

The deployment of second generation biomass increases in all models when going from REF to Tax30, as all models treat lignocellulosic biomass as a zero- or low-carbon fuel. Some authors have argued, however, that due to direct and indirect land-use change effects, emission reductions from biomass might be much smaller than expected [52–55]. It would be advisable to improve the existing models by fully including land-use into the assessment framework.

These substantially different mitigation pathways depend on the competition between different technologies based on model

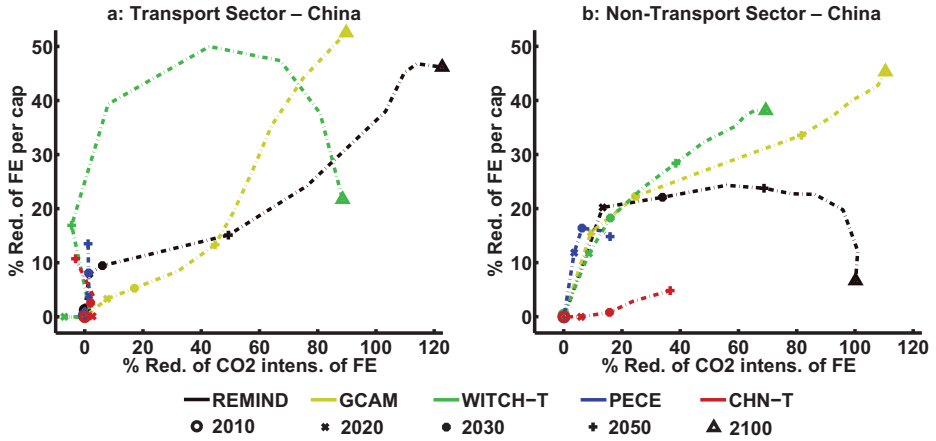


Fig. 9. Percentage reduction from REF to TAX30 of FE per Capita over CO_2 intensity per FE. The dots mark the years 2010, 2020, 2030, 2050, 2100.

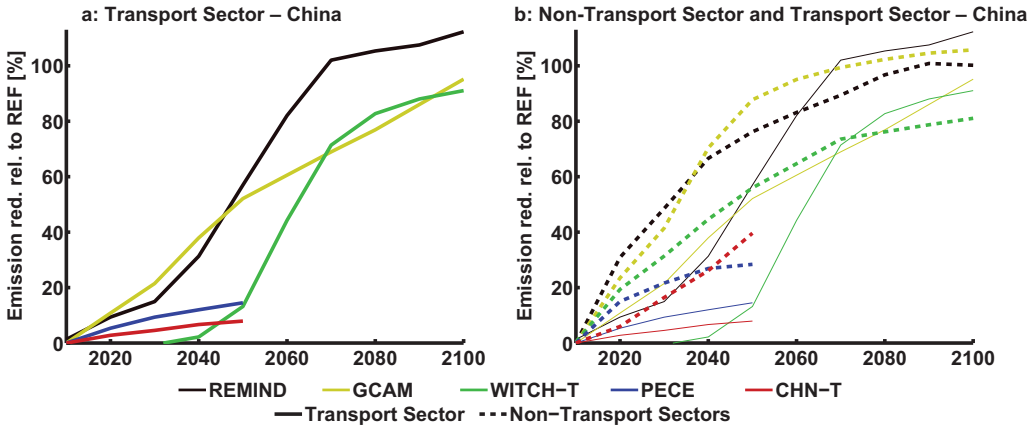


Fig. 10. Mitigation in TAX30 relative to REF in the different sectors.

assumptions about technology availability (e.g., no hydrogen use for transport in WITCH-T), conversion efficiencies, technology costs and constraints both on technology use and primary energy availability. The transport sector is deeply linked to the other energy sectors, thus the technology options and costs in all sectors matter. As one example, assumptions about carbon-free hydrogen availability or energy costs in the heat sector can strongly influence the use of biofuels in the transport sector [29].

4.2. Comparing decarbonization between transport and non-transport sectors

To find systematic differences between the transport and the non-transport sectors, the percentage reduction of FE per capita is plotted over the percentage reduction of CO_2 intensity of FE for both sectors (always comparing the values from TAX30 with REF) in Fig. 9. Such a split allows for a clear distinction of the different decarbonization visions of the different models. If a model is strongly in the upper left half of the figure, it mostly reduces final energy use while not decarbonizing the energy it uses, if it is in the lower right half, it mostly decarbonizes but does not reduce final energy use.

In the transport sector, the two partial-equilibrium models CHN-TIMES and PECE only use the option of decreasing final energy use, making their transport emissions quite stiff and unreactive to climate policies – much stiffer than the non-transport sectors where CHN-TIMES strongly decreases carbon intensity. REMIND and GCAM go the opposite way – after an initial reduction of FE demand, they mostly decrease the carbon intensity of their final energies, using decarbonized electricity as well as BioCCS for both liquid fuels and hydrogen production. WITCH-T shows a different dynamic, first strongly reducing the FE intensity by earlier electrification of the transport sector, and then decarbonizing the electricity sector in the second half of the century.

All models show a similar characteristic: the decarbonization of the transport sector strongly lags behind that of the other sectors. In Fig. 9, this can be seen in the position of the time markers – in the transport sector, most of the action happens after 2050, while in the non-transport sector, substantial reductions the time markers are more evenly spaced. It becomes even more apparent when comparing relative levels of mitigation in the transport and non-transport sectors in Fig. 10 A given level of relative mitigation is usually achieved 10–30 years later, with the largest time lag of initially 30 years showing in WITCH-T. CHN-TIMES and PECE also show a substantial lag, as transport never decarbonizes by more than 7 and 15% respectively. GCAM first shows a very small time lag of ~10 years which widens over time to >30 years, while REMIND shows a 10–20 year gap. This time lag is only reversed in REMIND around 2060 at mitigation levels above 80%, when the strong use of BioCCS liquids leads to higher negative emissions in the transport sector than in the non-transport sectors, and in WITCH-T around 2070, when the relative mitigation in the transport sector surpasses that of the other sectors as transport relies strongly on low-carbon electricity, while the non-transport sectors have substantial residual emissions from coal and oil.

When thinking of long-term sustainability, it is not only emission reductions that matter, but also the dependence on fossil resources. According to the models, this is another difference between the transport sector and the non-transport sectors: Over the second half of the century, all models see more than 43% of transport final energy coming from fossil resources. In the non-transport sectors, REMIND and GCAM manage to decrease the fossil share to much lower numbers between 15 and 26%. In WITCH-T, the story is somewhat different due to the incorporation of aviation in a fossil-fuel-heavy non-electricity sector (hence it is not present in the transportation sector results discussed within this paper) and the strong electrification of the freight sector. As a result, the fossil share of the transport sector can be reduced to levels below that in the non-transport sectors with electricity being sourced from low-carbon electricity in the latter part of the century.

5. Summary and conclusion

In this study, we have compared long-term transport energy demand and emission projections from five large-scale energy-economy models, as well as the models' reaction to a set of climate policies. Special focus was on i) analyzing the mitigation levers along the chain of causality from mobility to primary energy, and ii) discussing the structural differences between mitigation in the transport sector and the non-transport sectors. The analysis is based on full well-to-wheel emissions accounting. It should be noted that the results do not represent lower limits to decarbonization, but rather the reaction to carbon prices that span a plausible range.

The major findings were:

- The different models project very different decarbonization pathways. The type and amount of mitigation strongly depends

on the choice of technologies implemented and the structure of the model. One could thus interpret the participating models as studies of different possible futures in which certain options (battery electric vehicles, fuel cell vehicles, large-scale sustainable biomass use) become viable or not.

- In the first half of the century, transport decarbonization lags 10–30 years behind mitigation efforts in the non-transport sectors in all models when subject to the same monetary incentives to decarbonize. This trend is persistent in GCAM, whereas it is reversed in the second half of the century in REMIND and WITCH-T. All three models achieve substantial transport emission reductions of 90% and more in stringent climate policy scenarios.
- Even in the most stringent policy scenario, transport strongly relies on liquid fuels until 2050, with more than 85% of transport final energy coming from liquids even in the strongest climate policy in all models (except for WITCH-T, which incorporates aviation in a fossil-fuel-heavy non-electricity sector and hence does not account for aviation in the transportation sector results discussed within this paper).
- Early (pre-2050) emission reductions achieved in GCAM and REMIND beyond the efficiency improvements seen in all models can be mostly attributed to the use of biomass to produce liquid fuels, in strong climate policies in combination with CCS.
- The global models achieve deep long-term emission reductions through substantial use of very efficient battery electric or fuel cell vehicles. The very deep emission reductions of more than 90% of the reference emissions seen in stringent policy scenarios are realized through the reduction of the carbon intensity of the used final energies, either through clean electricity or BioCCS used for both liquid fuels and hydrogen.
- Both partial-equilibrium models focusing on China (PECE and CHN-TIMES) are less flexible in their reaction to climate policies, as they a) do not include reductions in mobility demand as a reaction to increased transportation costs, b) see only limited electrification of transport even under stringent climate policies and c) only use a limited amount of less carbon intensive primary energies (biomass) to produce liquid fuels, and do not combine them with CCS. Instead, they almost exclusively reduce emissions via use of more efficient vehicles.
- Apart from differing assumptions about the economic growth trends in China and US which drive differing energy service demands, the differences between models has a much stronger influence on the decarbonization path than the differences between regions. Thus, the choice of technologies implemented and the structure of the model determine a large part of the observed mitigation results.
- To prevent model artifacts and improve plausibility of the scenarios, the analyzed transport models should better incorporate all decarbonization options along the chain of causality, e.g., price-responsive mobility demand, better representation of modal shift, finer granularity of investments into vehicle efficiency, as well as more complete representation of the technological options to use advanced fuels (including hydrogen) in both passenger and freight sectors. Also, detailed comparisons with bottom-up scenarios are needed to validate the chosen parameterization.

It can be concluded that amongst the models studied, the hypothesis that the transport sector is more difficult to decarbonize than the non-transport sectors with a carbon price of plausible size is confirmed when looking at the time period before 2060. In the long run, however, the three global models achieve deep emission reductions by 90% and more in the strong climate policy scenario. This almost complete decarbonization hinges on the use of advanced vehicle technologies in combination with carbon-free primary energy sources; especially biomass combined with CCS plays a crucial role. The extent to which earlier mitigation is possible strongly depends on the choice of technologies implemented and the structure of the model, with both partial-equilibrium models proving to be less flexible.

One could thus interpret the different projections by the participating models as studies of different possible futures in which certain options (battery electric vehicles, fuel cell vehicles, large-scale sustainable biomass use) become viable or not, or in which behavioral trends are either broken or reinforced – e.g., the growth of freight transport and the shift to private mobility almost independent of prices.

Although the models clearly state that a carbon tax of a plausible size will not lead to strong near-term decarbonization in the transport sector, one should not conclude that near-term emission reductions are impossible. There is a substantial literature on other policies beside pricing carbon pricing that target consumer behavior and infrastructure and that can have a major influence on travel behavior and thus emissions (see Section 5.1). Most of the policies targeting mobility demand have long inertias – consumer behavior is slow to change [56], and infrastructure change or city compacting can take decades. If these policies are to contribute to emission reductions in the mid-term, they have to be started right away. Thus, while carbon pricing is necessary for achieving economy-wide deep long-term emission reductions, it should be complemented with region-specific and integrated policies aimed at changing mobility demand and promoting the use of and innovation in alternative transport options.

5.1. Caveats and future work

This study analyzes modeling results and thus is subject to all the caveats adhering to long-term energy-economic models. The strongest qualification is that all participating models are economic models that have cannot fully capture non-monetary costs and behavioral drivers. This is especially a problem when modeling transportation, as passenger transport is much more influenced by non-monetary drivers than, e.g., the choice of primary fuels in electricity generation. One major determinant is the speed of a travel mode, which only GCAM addresses explicitly by including the value of travel time into the costs that determine the choice of transport mode [22]. Behavioral aspects like habituation, status consumption, life styles or public acceptance, in combination with environmental factors, such as infrastructure availability and city design, have a substantial influence on the choice of both transport mode and vehicle used. Including these drivers in future policies may allow much easier mitigation action than through price signals alone and result in faster introduction of alternative transport options.

Banister et al. perform an in-depth theoretical analysis of transport decarbonization and come to the conclusion that substantial measures beyond carbon pricing and green infrastructure are necessary to achieve deep cuts in transport emissions. They diagnose that the current transport decarbonization research is limited by the strong influence from engineering and neoclassical economics, and emphasize the need to “rethink transport governance” and to include all possible interventions [5]. Some examples of these interventions follow. Policies disincentivizing single occupancy of LDVs can lead to a substantial reduction in emissions [57]. According to a review by Cairns et al., “soft mobility management” measures including teleworking, school travel plans and transport awareness campaigns can reduce overall traffic levels by about 11% within ten years [56]. Goodwin reviews a large group of policies all targeting passenger travel behavior and comes to the

conclusion that "the evidence available is rich concerning reductions in car use up to about 20%–30%" [58]. Bristow et al. require a combination of "soft" measures and price signals to reach stringent UK transport mitigation targets [59]. Tight et al. find a limit of about 20% reduction in passenger transport emissions that can be achieved by behavioral changes alone [60], while Anable et al. register a 58% reduction in 2050 UK transport CO_2 emissions achieved only by life style changes when coupling a storyline for pro-environmental life style change to a detailed transport model [61].

These studies point to relevant decarbonization options, but they also have their limitations: they have a local focus, the results are difficult to transfer or generalize, and they usually do not include empirical validation. For a fair evaluation of different policies, it would be necessary to have a quantitative understanding of the achieved impacts as well as the direct and indirect costs incurred through such policies like zoning, tolls, car license limitations, etc. More bottom-up research is needed to provide robust knowledge and consolidate the individual case studies into stylized facts for the transport sector.

Also not included in the current studies are local benefits due to reduced air pollution from advanced vehicles such as BEVs or FCVs. These local benefits can be substantial: Creutzig et al. analyzed the current transportation system in Beijing and found that social costs of air pollution are four times higher than those from climate change [62]. The implementation of emission-dependent road pricing or city-wide bans of high-emission vehicles that are targeted at local air pollution can help the spread of advanced technologies: The ban of gasoline-based scooters in many Chinese metropolitan areas has fostered the fast market penetration of electric two-wheelers.

An issue that is present in most of the models participating in this study is the lack of depth in the modeling of vehicle granularity and consumer heterogeneity. The participating models only differentiate between different vehicle technologies, not between different vehicle sizes, and they only model one consumer with a single set of preferences. Increasing fuel prices would incentivize reductions in vehicle size and weight, thus reducing final energy demand. Also, as the majority of trips, as well as the average daily driving distances are below 100 km, a subgroup of car owners might be willing to buy short-range electric cars, which then could act as enabling technology for BEVs [24]. In addition, strategic national industry policies might change the timing of technology deployment. According to some analyses, Chinese firms might better compete with German and US car manufacturers in the electric car industry than in internal combustion engine (ICE) technology. If such strategic thoughts induce a national government to supports its electric car industry, BEVs might penetrate the market much earlier than projected in the models.

Due to these limitations, the results can probably be interpreted as a conservative estimation of possible changes to vehicles and modal split. On the other hand, the global models seem rather optimistic on the substitution possibilities on the primary energy side, specifically the use of biomass liquids in combination with CCS.

To improve transport modeling, further research would be needed in the following areas: improved representation of price-elasticity of demand in the models that project price-insensitive mobility demand, improved differentiation between urban and intercity travel, more detailed modeling of modal shifts, representation of infrastructure network effects (both for the build-up of hydrogen/electric refueling infrastructure and for public transport systems), representation of additional transport policies targeting behavior and infrastructure, inclusion of local air pollution benefits, and engineering analysis of final energy substitution possibilities for freight, aviation and navigation – as seen above, the WITCH-T assumption that freight transport can be electrified at reasonable costs allows strong decarbonization of transport to occur without having to resort to BioCCS.

Acknowledgments

The research leading to these results has received funding from the EuropeAid – project "Climate Policy Outreach" (CPO). Page Kyle would like to acknowledge long-term support for GCAM development from the Integrated Assessment Research Program in the Office of Science of the U.S. Department of Energy.

References

[1] IPCC. Climate change 2007: synthesis report. Intergovernmental Panel on Climate Change; 2007.
[2] IEA. World energy outlook 2012. Paris: International Energy Agency; 2012.
[3] Schäfer A, Jacoby HD. Vehicle technology under CO_2 constraint: a general equilibrium analysis. Energy Policy Jun. 2006;34(9):975–85.
[4] Barker T, Bashmakov I, Alharthi A, Amann M, Cifuentes L, Drexhage J, et al. Mitigation from a cross-sectoral perspective. In: Metz B, Davidson OR, Bosch PR, Dave R, Meyer LA, editors. Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel of Climate Change. Cambridge, United Kingdom and New York, NY, USA: Cambrigde University Press; 2007.
[5] Banister D, Anderton K, Bonilla D, Givoni M, Schwanen T. Transportation and the Environment. Ann Rev Environ and Resour 2011;36(1):247–70.
[6] Luderer G, Bosetti V, Jakob M, Leimbach M, Steckel J, Waisman H, et al. The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison. Clim Change 2011:1–29.
[7] Luderer G, Pietzcker RC, Kriegler E, Haller M, Bauer N. Asia's role in mitigating climate change: a technology and sector specific analysis with ReMIND-R. Energy Econ Dec, 2012;34(Suppl. 3):S378–90. 0.
[8] van Vliet OPR, Faaij APC, Turkenburg WC. Fischer–Tropsch diesel production in a well-to-wheel perspective: a carbon, energy flow and cost analysis. Energy Convers Manag Apr. 2009;50(4):855–76.
[9] Liu G, Larson ED, Williams RH, Kreutz TG, Guo X. Making Fischer–Tropsch fuels and electricity from coal and biomass: performance and cost analysis. Energy Fuels Jan. 2011;25(1):415–37.
[10] Mantripragada HC, Rubin ES. CO_2 implications of coal-to-liquids (CTL) plants. Int J Greenh Gas Control Aug. 2013;16:50–60.
[11] Schafer A, Victor DG. Global passenger travel: implications for carbon dioxide emissions. Energy Aug. 1999;24(8):657–79.
[12] Schafer A, Victor DG. The future mobility of the world population. Transport Res Part A Policy Pract Apr. 2000;34(3):171–205.
[13] Kloess M, Müller A. Simulating the impact of policy, energy prices and technological progress on the passenger car fleet in Austria—a model based analysis 2010–2050. Energy Policy Sep. 2011;39(9):5045–62.
[14] Brand C, Tran M, Anable J. The UK transport carbon model: an integrated life cycle approach to explore low carbon futures. Energy Policy Feb. 2012;41(0):107–24.
[15] McCollum D, Yang C, Yeh S, Ogden J. Deep greenhouse gas reduction scenarios for California – strategic implications from the CA-TIMES energy-economic systems model. Energy Strateg Rev Mar. 2012;1(1):19–32.
[16] Liu W, Lund H, Mathiesen BV. Modelling the transport system in China and evaluating the current strategies towards the sustainable transport development. Energy Policy Jul. 2013;58:347–57.
[17] Ridjan I, Mathiesen BV, Connolly D, Dui&cacute N. The feasibility of synthetic fuels in renewable energy systems. Energy Aug. 2013;57:76–84.
[18] Meyer I, Leimbach M, Jaeger CC. International passenger transport and climate change: a sector analysis in car demand and associated emissions from 2000 to 2050. Energy Policy Dezember 2007;35(12):6332–45.
[19] Mathiesen BV, Lund H, Nørgaard P. Integrated transport and renewable energy systems. Util Policy Jun. 2008;16(2):107–16.
[20] Grahn M, Azar C, Williander MI, Anderson JE, Mueller SA, Wallington TJ. Fuel and vehicle technology choices for passenger vehicles in achieving stringent CO_2 targets: connections between transportation and other energy sectors. Environ Sci Technol May 2009;43(9):3365–71.
[21] Gül T, Kypreos S, Turton H, Barreto L. An energy-economic scenario analysis of alternative fuels for personal transport using the Global Multi-regional MARKAL model (GMM). Energy Oct. 2009;34(10):1423–37.
[22] Kyle P, Kim SH. Long-term implications of alternative light-duty vehicle technologies for global greenhouse gas emissions and primary energy demands. Energy Policy May 2011;39(5):3012–24.
[23] Juul N, Meibom P. Optimal configuration of an integrated power and transport system. Energy May 2011;36(5):3523–30.
[24] Densing M, Turton H, Bäuml G. Conditions for the successful deployment of electric vehicles – a global energy system perspective. Energy Nov. 2012;47(1):137–49.

[25] Bosetti V, Longden T. Light duty vehicle transportation and global climate policy: the importance of electric drive vehicles. Energy Policy Jul. 2013;58:209–19.

[26] Girod B, van Vuuren DP, Deetman S. Global travel within the 2 °C climate target. Energy Policy Jun. 2012;45(0):152–66.

[27] Azar C, Lindgren K, Andersson BA. Global energy scenarios meeting stringent CO_2 constraints—cost-effective fuel choices in the transportation sector. Energy Policy Aug. 2003;31(10):961–76.

[28] Grahn M, Azar C, Lindgren K. The role of biofuels for transportation in CO_2 emission reduction scenarios with global versus regional carbon caps. Biomass Bioenergy Mar. 2009;33(3):360–71.

[29] Grahn M, Azar C, Lindgren K, Berndes G, Gielen D. Biomass for heat or as transportation fuel? A comparison between two model-based studies. Biomass Bioenergy Nov. 2007;31(11–12):747–58.

[30] Cuenot F, Fulton L, Staub J. The prospect for modal shifts in passenger transport worldwide and impacts on energy use and CO_2. Energy Policy Feb. 2012;41(0):98–106.

[31] Chen W. The costs of mitigating carbon emissions in China: findings from China MARKAL-MACRO modeling. Energy Policy May 2005;33(7):885–96.

[32] Chen W, Wu Z, He J, Gao P, Xu S. Carbon emission control strategies for China: A comparative study with partial and general equilibrium versions of the China MARKAL model. Energy Jan. 2007;32(1):59–72.

[33] Chen W, Li H, Wu Z. Western China energy development and west to east energy transfer: application of the Western China sustainable energy development model. Energy Policy Nov. 2010;38(11):7106–20.

[34] Kim SH, Edmonds J, Lurz J, Smith S, Wise M. The object-oriented energy climate technology systems (ObjECTS) framework and hybrid modeling of transportation in the MiniCAM long-term, global integrated assessment model. The Energy J 2006:63–91.

[35] Zou J, Fu S. China human development Report 2009/10: China and a sustainable future, towards a low carbon economy & society. Commissioned by UNDP China. Beijing: China Translation & Publishing Corporation; 2010 (both in Chinese and English), 2010.

[36] Fu S, Zou J, Wang K. Scenario study on China's low carbon future and technology option based on a bottom-up model. In: Presented at the 34th IAEE International Conference and 2011 international energy workshop 2011.

[37] Luderer G, Pietzcker RC, Bertram C, Kriegler E, Meinshausen M, Edenhofer O. Economic mitigation challenges: how further delay closes the door for achieving climate targets. Environ. Res. Lett. Sep. 2013;vol. 8(no. 3):034033.

[38] Luderer G, Leimbach M, Bauer N, Kriegler E, Aboumahboub T, Curras TA, Baumstark L, Bertram C, Giannousakis A, Hilaire J, Klein D, Mouratiadou I, Pietzcker R, Piontek F, Roming N, Schultes A, Schwanitz VJ, Strefler J. Description of the REMIND Model (Version 1.5); August 19, 2013. Available at SSRN: http://ssrn.com/abstract=2312844 or http://dx.doi.org/10.2139/ssrn.2312844.

[39] Bosetti V, Carraro C, Galeotti M, Massetti E, Tavoni M. WITCH: A World Induced Technical Change Hybrid Model. The Energy Journal, Special Issue on Hybrid Modeling of Energy-Environment Policies: Reconciling Bottom-up and Top-down:13–38 2006.

[40] Bosetti V, Longden T. Light duty vehicle transportation and global climate policy: the importance of electric drive vehicles. Milan: FEEM Working Paper; 2012.

[41] Longden T. Deviations in kilometres travelled: the impact of different mobility futures on energy use and climate policy. Milan: FEEM Working Paper; 2012.

[42] Zahavi Y, Beckmann MJ, Golob TF. The "UMOT"/urban interactions. Washington, D.C.: Springfield, Va.: U.S. Dept. of Transportation, Research and Special Programs Administration, Systems Analysis Division; National Technical Information Service [distributor]; 1981.

[43] Mokhtarian PL, Chen C. TTB or not TTB, that is the question: a review and analysis of the empirical literature on travel time (and money) budgets. Transport Res Part A Policy Pract Nov. 2004;38(9–10):643–75.

[44] Hao H, Wang H, Yi R. Hybrid modeling of China's vehicle ownership and projection through 2050. Energy Feb. 2011;36(2):1351–61.

[45] UN. World population prospects: the 2010 revision (CD-ROM edition). United Nations, Department of Economic and Social Affairs.; 2010.

[46] US Dept of Transport. National transportation statistics: table 1–11: number of U.S. Aircraft, vehicles, vessels, and other conveyances [Online]. Available from: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/html/table_01_11.html; 2012 [accessed 23.08.13].

[47] Statistics Bureau Japan. Statistical handbook of Japan: table 9.2-number of motor vehicles owned [Online]. Available from: http://www.stat.go.jp/english/data/handbook/c09cont.htm; 2012 [accessed 23.08.13].

[48] Eurostat. Real GDP per capita, growth rate and totals [Online]. Available from: http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=0&language=en&pcode=tsdec100; 2013 [accessed 23.08.13].

[49] Oak Ridge National Laboratory. Table 3.6-vehicles per thousand people in the United States, 1900–2010 [Online]. Available, http://cta.ornl.gov/data/tedb32/Spreadsheets/Table3_06.xls; 2013 [accessed 23.08.13].

[50] Eurostat. Motorisation rate – cars per 1 000 inhabitants [Online]. Available from: http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=0&language=en&pcode=tsdpc340; 2013 [accessed 23.08.13].

[51] Calvin K, Clarke L, Krey V, Blanford G, Jiang K, Kainuma M, et al. The role of Asia in mitigating climate change: results from the Asia modeling exercise. Energy Econ Dec. 2012;34(Suppl. 3):S251–60.

[52] Fargione J, Hill J, Tilman D, Polasky S, Hawthorne P. Land clearing and the biofuel carbon debt. Science Feb. 2008;319(5867):1235–8.

[53] Searchinger TD, Hamburg SP, Melillo J, Chameides W, Havlik P, Kammen DM, et al. Fixing a critical climate accounting error. Science Oct. 2009;326(5952):527–8.

[54] Melillo JM, Reilly JM, Kicklighter DW, Gurgel AC, Cronin TW, Paltsev S, et al. Indirect emissions from biofuels: how important? Science Dec. 2009;326(5958):1397–9.

[55] Creutzig F, Popp A, Plevin R, Luderer G, Minx J, Edenhofer O. Reconciling top-down and bottom-up modelling on future bioenergy deployment. Nat Clim Change May 2012;2(5):320–7.

[56] Cairns S, Sloman L, Newson C, Anable J, Kirkbride A, Goodwin P. Smarter choices: assessing the potential to achieve traffic reduction using 'Soft measures'. Transport Rev 2008;28(5):593–618.

[57] Horne M, Jaccard M, Tiedemann K. Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions. Energy Econ Jan. 2005;27(1):59–77.

[58] Goodwin P. Policy incentives to change behaviour in passenger transport [Online]. Available from: http://www.internationaltransportforum.org; May-2008 [accessed 14.12.12].

[59] Bristow AL, Tight M, Pridmore A, May AD. Developing pathways to low carbon land-based passenger transport in Great Britain by 2050. Energy Policy Sep. 2008;36(9):3427–35.

[60] Tight MR, Vicat A, Bristow AL, Pridmore A, May AD. An exploration of household response to personal travel carbon-reduction targets. Int J Sustain Transport 2007;1(3):143–59.

[61] Anable J, Brand C, Tran M, Eyre N. Modelling transport energy demand: a socio-technical approach. Energy Policy Feb. 2012;41(0):125–38.

[62] Creutzig F, He D. Climate change mitigation and co-benefits of feasible transport demand policies in Beijing. Transport Res Part D Transport Environ Mar. 2009;14(2):120–31.

Chapter 6

Economic mitigation challenges: how further delay closes the door for achieving climate targets*

Gunnar Luderer
Robert Carl Pietzcker
Christoph Bertram
Elmar Kriegler
Malte Meinshausen
Ottmar Edenhofer

*published in *Environmental Research Letters* as Luderer, G., Pietzcker, R.C., Bertram, C., Kriegler, E., Meinshausen, M., Edenhofer, O. (2013) "Economic mitigation challenges: how further delay closes the door for achieving climate targets". Environ. Res. Lett. 8, 034033
dx.doi.org/10.1088/1748-9326/8/3/034033

OPEN ACCESS
IOP PUBLISHING ENVIRONMENTAL RESEARCH LETTERS
Environ. Res. Lett. **8** (2013) 034033 (8pp) doi:10.1088/1748-9326/8/3/034033

Economic mitigation challenges: how further delay closes the door for achieving climate targets

Gunnar Luderer[1], Robert C Pietzcker[1], Christoph Bertram[1], Elmar Kriegler[1], Malte Meinshausen[1,2] and Ottmar Edenhofer[1,3,4]

[1] Potsdam Institute for Climate Impact Research, D-14473 Potsdam, Germany
[2] School of Earth Sciences, University of Melbourne, Victoria 3010, Australia
[3] Technische Universität Berlin, D-10632 Berlin, Germany
[4] Mercator Research Institute on Global Commons and Climate Change, D-10829 Berlin, Germany

E-mail: luderer@pik-potsdam.de

Received 5 May 2013
Accepted for publication 28 August 2013
Published 17 September 2013
Online at stacks.iop.org/ERL/8/034033

Abstract
While the international community aims to limit global warming to below 2 °C to prevent dangerous climate change, little progress has been made towards a global climate agreement to implement the emissions reductions required to reach this target. We use an integrated energy–economy–climate modeling system to examine how a further delay of cooperative action and technology availability affect climate mitigation challenges. With comprehensive emissions reductions starting after 2015 and full technology availability we estimate that maximum 21st century warming may still be limited below 2 °C with a likely probability and at moderate economic impacts. Achievable temperature targets rise by up to ∼0.4 °C if the implementation of comprehensive climate policies is delayed by another 15 years, chiefly because of transitional economic impacts. If carbon capture and storage (CCS) is unavailable, the lower limit of achievable targets rises by up to ∼0.3 °C. Our results show that progress in international climate negotiations within this decade is imperative to keep the 2 °C target within reach.

Keywords: climate change mitigation, 2 °C target, delayed climate policy, low-carbon technologies

S Online supplementary data available from stacks.iop.org/ERL/8/034033/mmedia

1. Introduction

Climate change is a major global challenge (IPCC 2007). The ultimate goal stated in the United Nations Framework Convention on Climate Change is to 'prevent dangerous anthropogenic interference with the climate system' (UNFCCC 1992). The international community adopted the long-term target of limiting the increase of global mean temperature to no more than 2 °C relative to pre-industrial levels. However, progress in the implementation of concrete emissions reduction policies has been slow. Even with the implementation of climate policy measures in several world regions, global emissions have continued to rise (Peters *et al* 2013, JRC/PBL 2012). Reaching the 2 °C target with high likelihood implies a tight limit on cumulative future anthropogenic greenhouse gas (GHG) emissions (Meinshausen *et al* 2009). Various reports have concluded that pledged national 2020 reduction targets fall short of the reductions required to meet the 2 °C target in a cost-optimal way (Höhne *et al* 2012, Rogelj *et al* 2010).

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

The decarbonization of economies requires a massive transformation in the way energy is produced and used (Fisher *et al* 2007, GEA 2012). Currently, the deployment of many low-carbon technologies faces technological difficulties or limited political support. For instance, carbon capture and storage (CCS), large-scale bioenergy production and nuclear energy are subject to sustainability concerns and public opposition. Similarly, integrating major shares of wind and solar power is challenging because of fluctuating supply from these sources.

In the past most climate mitigation scenarios were prepared under the idealistic assumptions of full flexibility in technology choice, globally coordinated climate policies ensuring that emission abatement would occur where it is cheapest, and the immediate start of climate policies (Fisher *et al* 2007, Knopf *et al* 2011). Meanwhile, several studies have considered climate mitigation scenarios with restricted technology portfolios (Edenhofer *et al* 2010, Azar *et al* 2010, Tavoni *et al* 2012), while others have investigated climate stabilization after a period of fragmented and delayed climate policy (Clarke *et al* 2009, Luderer *et al* 2012a, Jakob *et al* 2012, van Vliet *et al* 2012, IEA 2009). These studies showed that both technology availability and fragmented climate policy have a strong effect on the cost and achievability of climate targets. Only a few studies have analyzed the combined effects of delayed action and technology failure (Rogelj *et al* 2013a, 2013b, van Vliet *et al* 2012).

This study fills crucial research gaps. Currently available studies have almost exclusively used inter-temporally aggregated mitigation costs and carbon prices as indicators of mitigation effort. However, policymakers are much more concerned about the shorter term effects and distributional impacts of mitigation policies. Our work quantifies the trade-offs between the stringency of long-term climate targets on the one hand, and policy-relevant socio-economic challenges such as transitory costs, short-term energy price increases, and the potential redistribution of wealth induced by a global cap-and-trade regime on the other. By analyzing the impact of climate policy frameworks on these economic mitigation challenges, we examine how a further delay of global action forecloses long-term stabilization levels and technology choices.

2. Methods

We used the integrated energy–economy–climate model REMIND to produce a large ensemble of 285 scenario experiments, which combine different assumptions on (a) technology availability, (b) the start date of comprehensive global climate policies, and (c) globally harmonized carbon price levels.

2.1. Modeling framework

REMIND is an inter-temporal general equilibrium model of the macro-economy with a technology-rich representation of the energy system (Leimbach *et al* 2009, Bauer *et al* 2012, Luderer *et al* 2012b). It represents capacity stocks of more than 50 conventional and low-carbon energy conversion technologies, including technologies for generating negative emissions by combining bioenergy use with carbon capture and storage (BECCS). REMIND accounts for relevant path-dependencies, such as the build-up of long-lived capital stocks, as well as learning-by-doing effects and inertias in the up-scaling in innovative technologies. These path-dependencies are of particular importance for the study of energy transformation pathways in general and delayed action scenarios like the ones considered here in particular. REMIND represents 11 world regions, and operates in time-steps of five years in 2005–2060, and ten years for the rest of the century.

To examine the carbon cycle and climate system response to emissions, we employ a probabilistic setup of the reduced complexity climate model MAGICC (Wigley and Raper 2001, Meinshausen *et al* 2009, 2011). A detailed description of the modeling framework is available in the supplementary information (SI) section 1 (available at stacks.iop.org/ERL/8/034033/mmedia).

There are important caveats to the use of an economic model for the analysis of global, long-term mitigation pathways. For instance, the societal choices and behavioral patterns that drive energy supply and demand can be, unlike physical laws, subject to change and are therefore inherently difficult to predict (Koomey 2002). Similarly, the development and performance of energy supply technologies is highly uncertain. Our analysis should therefore not be mistaken for a *prediction* of future developments, but rather a strategic exploration of climate policy options based on a set of mitigation *scenarios*. As described in section 2.2, we use a large number of scenarios with different technology and policy assumptions to cover a wide spectrum of plausible climate futures.

2.2. Scenario definition

Along the policy-timing dimension, we consider three scenarios *Frag2015, Frag2020* and *Frag2030* with delayed adoption of cooperative mitigation action with globally harmonized GHG pricing resulting in comprehensive emissions reductions, assuming that climate policies remain weak and fragmented until 2015, 2020 and 2030 (cf figure 3(a)), respectively. In the time-steps before the start of cooperative action, world regions are assumed to follow a weak, fragmented climate policy regime based on a weak interpretation of the pledges or reduction proposals under the Cancun Agreements or Copenhagen Accord for 2020, and an extrapolation of the implied climate policy ambition beyond 2020 (*WeakPol* reference scenario, see SI section 6 (available at stacks.iop.org/ERL/8/034033/mmedia) and Luderer *et al* 2013). The *WeakPol* scenario yields similar global emissions by 2020 as the full implementation of the unconditional pledges under lenient accounting rules (UNEP 2012). While *Frag2015* marks an optimistic possible outcome of the current climate negotiations with a 2015 climate agreement resulting in enhanced reductions in 2020, *Frag2030* is a possible outcome of a failure of the current round of climate negotiations, with a continuation of weak and fragmented climate policies until 2030. In addition, we consider a

(hypothetical) *immediate*, scenario with global comprehensive emissions reductions effective and implemented from 2015 onwards.

Along the scenario dimension of technology availability, we consider seven alternative cases, similar to those used in Kriegler *et al* (2013): (i) *default*—full technology portfolio, (ii) *NoCCS*—unavailability of CCS, (iii) *NoBECCS*—unavailability of CCS in combination with bioenergy (BECCS), (iv) *LimBio*—reduced bioenergy potential (100 EJ compared to 300 EJ in all other cases), (v) *NucPO*—phase out of investments into nuclear energy, (vi) *LimSW* —penetration of solar and wind power limited to 20%, and (vii) *LowEI*—lower energy intensity, with final energy demand per economic output decreasing faster than historically observed.

For each combination of technology and climate policy assumptions, we ran ten scenarios covering a wide spectrum of globally harmonized CO_2 price levels adopted after the start of comprehensive climate policies[5]. Globally harmonized CO_2 prices increase at 5% p.a., resulting in near cost-optimal inter-temporal emissions reductions to achieve a given long-term climate target (see SI section 5 for a discussion of the sensitivity of results to climate policy formulation available at stacks.iop.org/ERL/8/034033/mmedia). These scenarios yield a wide range of responses in the economy and the climate system. In addition, we performed some scenario experiments with a prescribed cumulative 2010–2100 GHG budget. They allow contrasting results from different scenarios with comparable climate outcomes. A more detailed description of the scenario setup is provided in SI section 2 (available at stacks.iop.org/ERL/8/034033/mmedia).

2.3. Economic indicators of mitigation challenge

We use four economic indicators to capture the breadth of economic and institutional challenges of stringent climate policies, and their dependence on the timing of climate policies and technology availability. (i) *Aggregated mitigation costs* are a commonly used proxy indicator of the long-term effects of climate policies. We define them here as macro-economic consumption losses aggregated with a discount rate of 5% over the time horizon 2010–2100, relative to aggregated and discounted gross world product (GWP). In addition, we use (ii) *transitional growth reduction*, defined as the maximum reduction of decadal consumption growth induced by climate policies in percentage points (pp) as a proxy of potential short-term disruptions during the phase-in of climate policies; (iii) *carbon market value*, defined as the aggregated and discounted value of greenhouse gases emitted from 2010–2100, as a proxy for the potential distributional conflicts when defining the regional and sectoral burden sharing under a comprehensive cap-and-trade regime; and (iv) the short-term *energy price increase* induced by climate policies, measured in terms of an aggregated global final energy price index, as a proxy for the effect of climate policies on the energy bills of households and firms. These indicators allow us to assess not only the long-term mitigation challenges, but also the challenges encountered at time-scales that are more relevant for today's decision-makers. SI section 3 (available at stacks.iop.org/ERL/8/034033/mmedia) provides the technical details on these indicators, and the rationale behind the parameter ranges chosen. Note that these economic indicators only measure efforts related to emissions reductions, but do not account for avoided damages or co-benefits of climate change mitigation.

[5] CO_2 prices exhibit strong regional differences in the *Frag2015, Frag2020* and *Frag2030* scenarios until 2015, 2020 and 2030 respectively, and converge to the globally harmonized level thereafter.

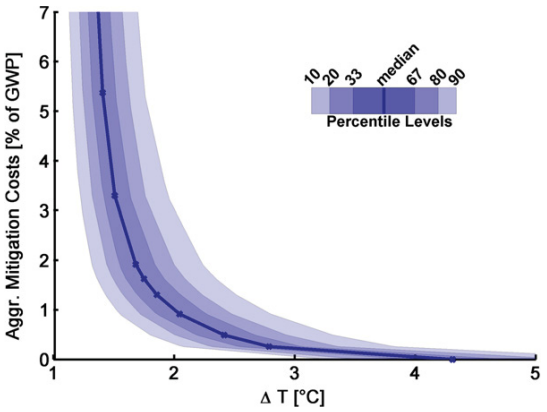


Figure 1. The 'achievability frontier' describing the trade-off between maximum 21st century surface air temperature increase and aggregated mitigation costs for the *Frag2015* scenario with *default* technology assumptions. Shaded bands show uncertainty ranges of the climate system's response to anthropogenic activities.

3. Results

3.1. Temperature-cost-trade-off curves

Relating mitigation to maximal temperature increase until 2100 establishes temperature-cost-trade-off curves, as shown in figure 1. The lower the maximal temperature over the 21st century, the higher the inter-temporally aggregated mitigation costs as a share of GWP. This property gives rise to the notion of an economic achievability frontier, i.e., a lower limit of achievable climate targets for a given macro-economic cost level. The temperature-cost-trade-off curves are highly convex, i.e., costs increase disproportionally with the increasing stringency of the long-term temperature target.

The climate system's response to anthropogenic emissions is subject to substantial uncertainties, which we address explicitly. In the *Frag2015* scenario with *default* technology assumptions, limiting global warming to below 2 °C with a 50% likelihood (ΔT_{50}) results in long-term mitigation costs of around 1.0% of GWP. Reaching the target with a likelihood of two-thirds (ΔT_{67}) implies long-term costs of 1.4%. We find a very tight, approximately linear relationship $\Delta T_{50} = 0.901\Delta T_{67} + 0.021\,°C$ (cf figure S5 available at stacks.iop.org/ERL/8/034033/mmedia), based on which these two confidence levels can be easily converted into each other.

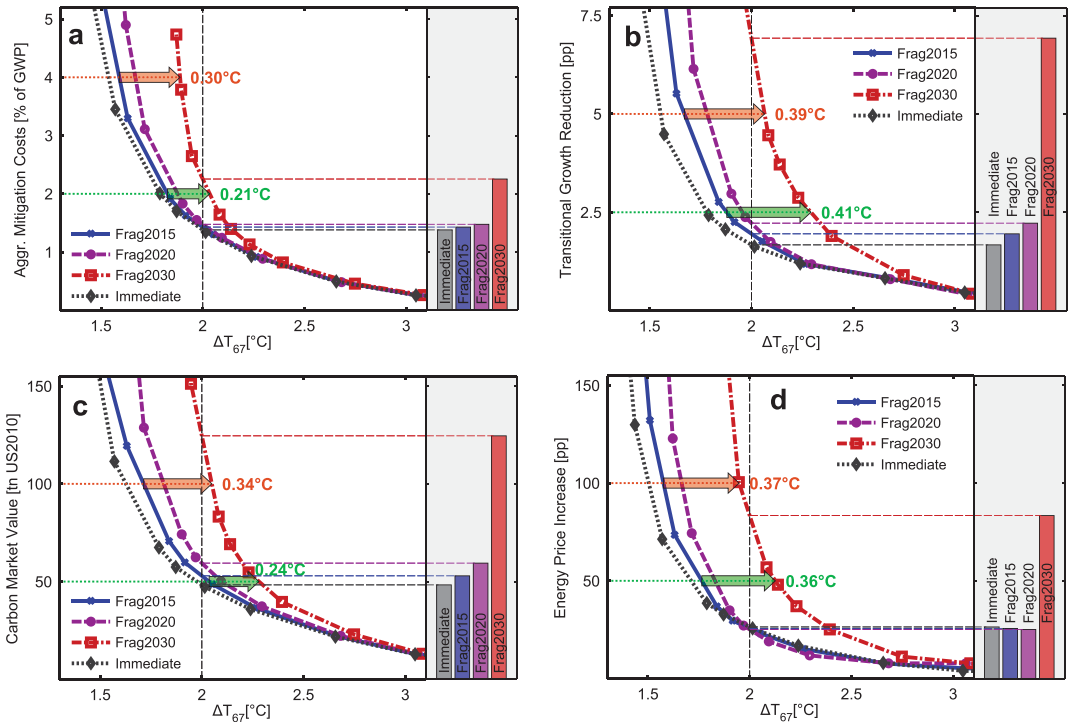


Figure 2. Temperature-cost-trade-off curves showing the effect of timing of global comprehensive mitigation action on (a) aggregated mitigation costs, (b) transitional consumption growth reductions, (c) carbon market value, and (d) energy price increase (*default* technology assumptions). *X*-axis shows temperature targets (maximum 2010–2100 temperatures) reached with a 67% likelihood. Bar charts indicate economic challenge of limiting warming to 2 °C.

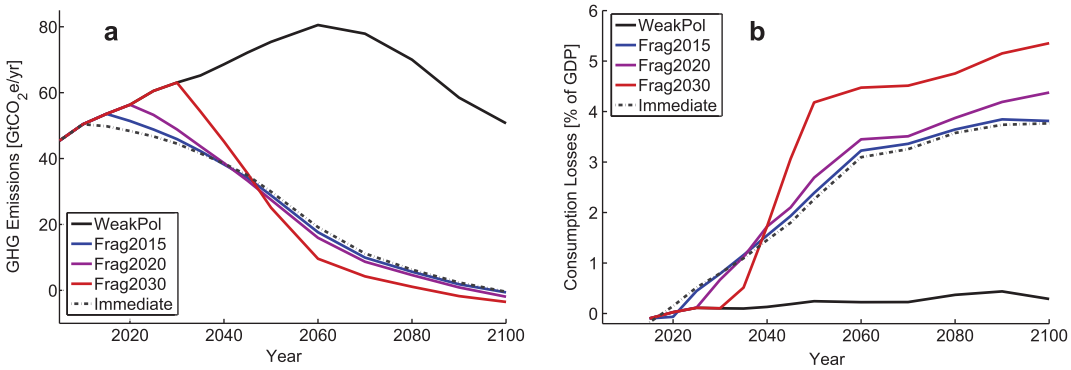


Figure 3. (a) Emission pathways and (b) consumptions losses for the reference scenario with weak polices (WeakPol), as well as for stabilization scenarios with a cumulative emissions budget of 2500 $GtCO_2e$, with immediate (immediate) or delayed implementation of comprehensive emissions reductions (*Frag2015, Frag2020, Frag2030*).

In the remainder of this letter, temperature targets refer to levels achieved with 67% likelihood.

3.2. Effect of delayed action

For all economic mitigation challenge indicators, a further deferral of comprehensive global emissions reductions results in a shift of the temperature-cost-trade-off curves towards higher costs and higher temperatures (figure 2). Thus, a delay of comprehensive climate policies implies not only higher costs for reaching a given climate target (bar charts), but also an increase of the lower level of climate targets achievable within the range of acceptable cost levels, as indicated by the arrows in the figure. For climate targets around 2 °C, the effects of delay on inter-temporally aggregated costs are substantial. This is in spite of the fact that lower costs in the short-term partially offset the higher long-term costs, which are subject to greater discounting (figure 3(b))[6].

[6] Since mitigation costs as a share of GWP increase over time, aggregated mitigation costs depend on the discount rate used for the inter-temporal aggregation. The sensitivity studies shown in SI section 4 (available at stacks.iop.org/ERL/8/034033/mmedia) demonstrate that lower discount rates result in higher mitigation costs and stronger effects of delayed action, but do not change the qualitative conclusions of the analysis.

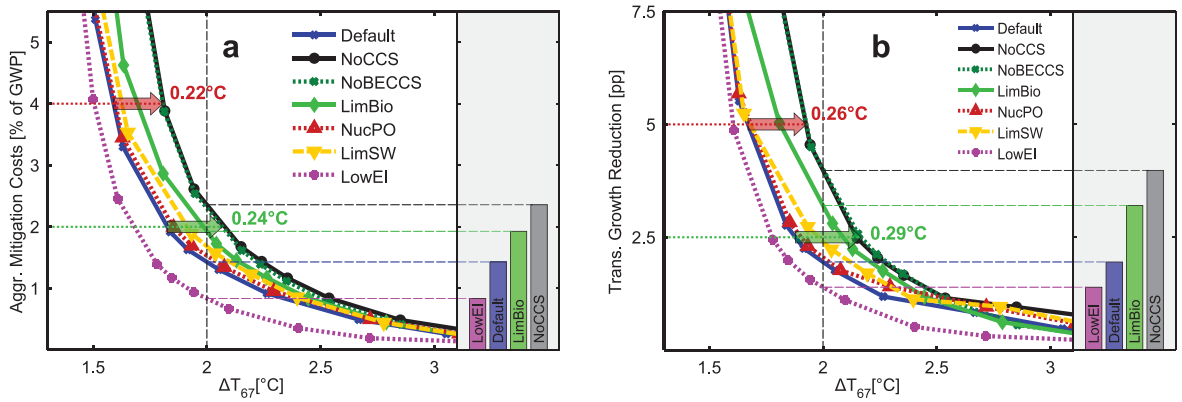


Figure 4. Temperature-cost-trade-off curves showing the effect of technology availability on (a) aggregated mitigation costs, and (b) transitional growth reduction (*Frag2015* scenario). Temperature targets (maximum 2010–2100 temperatures) reached with a 67% likelihood. Bar charts indicate economic challenges of limiting warming to 2 °C.

The longer the climate policy regime remains weak and fragmented, the higher are the emissions reduction rates required after the implementation of comprehensive climate policies to reach low stabilization targets (figure 3(a), see also Stocker 2012). This is mirrored in the development of policy costs measured in terms of consumption losses over time, which show an abrupt increase of costs in case of cooperative action delayed beyond 2030 (figure 3(b)). The effect of delay on the transitional growth reduction after implementation of comprehensive emissions reductions is therefore even more pronounced than the effect on aggregated mitigation costs. For aggregated mitigation costs in the range of 2–4% of GWP, lowest achievable climate targets in *Frag2030* exceed those found for *Frag2015* by 0.2–0.3 °C. For transitional mitigation costs in the range of 2.5–5 pp, the shift even amounts to ∼0.4 °C. Recent macro-economic data suggest that a short-term growth reduction of 5 pp is comparable to the effect of the financial crisis (IMF 2012). We also find that transitional costs for limiting warming to 2 °C is three times higher in case of *Frag2030* than in *Frag2015*.

The impact of mitigation timing on short-term energy price increases is similar to that on the transitional growth reductions. Lowest climate targets achievable at energy price increases of 50–100 pp shift by almost 0.4 °C if climate policies remain weak and fragmented until 2030 (figure 2(d)). Increases of final energy prices in comparable magnitude have been observed in the past for individual regions or energy carriers (see SI section 3 available at stacks.iop.org/ERL/8/034033/mmedia). In case of full technology availability, the short-term energy price increase induced by climate policies consistent with 2 °C stabilization remains moderate at around 25 pp even in the *Frag2020* scenario, but more than thrice this value in *Frag2030*.

Carbon pricing—which ensures economic efficiency (Fisher *et al* 1996)—emerges as a crucial institutional challenge. If the 2 °C target is implemented in the *Frag2015* scenario, the cumulated present value of emissions permits in 2010–2100 amounts to US$ ∼50 trillion, which is comparable to the market value of crude oil consumed over the same period in the baseline scenario without climate policy. If action is delayed beyond 2030, the carbon market value implied by 2 °C stabilization more than doubles, and lowest climate targets achievable at cumulated carbon market values of US$ 50–100 trillion shift by ∼0.3 °C.

3.3. Effect of technology availability

We focus the further discussion on aggregated mitigation costs and transitional growth reduction (figures 4 and 5). Insights for carbon market value and energy price increases are qualitatively similar and shown in figures S2 and S7 (available at stacks.iop.org/ERL/8/034033/mmedia). We observe that the availability of CCS technologies has a strong influence on target achievability. Lowest achievable mitigation targets increase by 0.2–0.3 °C if CCS cannot be used. Limited bioenergy potential also results in a significant shift in the temperature-cost-trade-off curves. The similarity of the results of (a) unavailability of BECCS and (b) unavailability of both BECCS and fossil CCS underscores the importance of negative emissions, and suggests that BECCS is more crucial for low stabilization than fossil CCS. A variety of alternative low-carbon options for electricity production is available; therefore, limitations on nuclear or wind and solar power have relatively small economic effects. By contrast, if economies increase their energy efficiency at a higher rate than has been historically observed, costs for reaching the 2 °C target decrease by 40%, and even lower climate targets become achievable already at moderate costs.

3.4. Targets achieved with temporary temperature overshoot

So far, we focused on climate outcomes in terms of maximal temperature increases over the 21st century. This is equivalent to formulating climate targets as not-to-exceed. Alternatively, 2100 temperature levels can be considered, equivalent to allowing for temporary overshooting of the long-term climate target. For the high end of mitigation cost levels, and if biomass and CCS are available, we observe that in terms

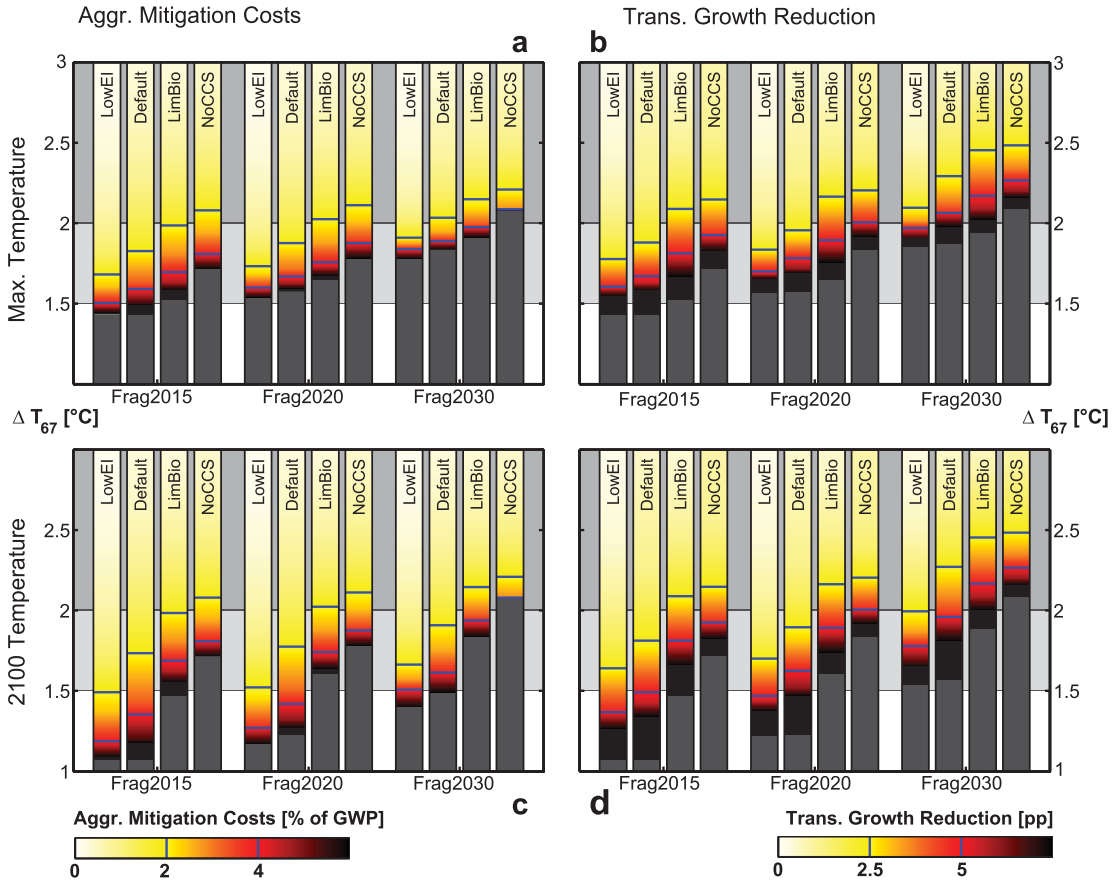


Figure 5. Overview of the combined effects of mitigation timing and technology availability on achievability of either not-to-exceed targets (in terms of maximum 2010–2100 temperature increase, upper panels), or 2100 temperature targets that allow for temporary overshoot (lower panels). Graphs show economic challenges (color shading) in terms of aggregated policy costs (left panels (a), (c)), and transitional growth reduction (right panels (b), (d)), as a function of temperature targets reached with 67% likelihood. Dark gray areas at the base of bars indicate temperature target levels that were not achieved with the range of carbon price paths assumed.

of 2100 temperatures considerably lower climate targets can become achievable than in terms of maximal 2000–2100 temperatures (figures 5 and S7, S8 available at stacks.iop.org/ERL/8/034033/mmedia). In the *Frag2015* scenario with default technology assumptions, 2100 temperatures achievable with 67% likelihood at aggregated costs of 4% of GWP drop to 1.35 °C, compared to 1.6 °C in terms of maximum 2000–2100 temperatures. The results also show that technology availability has a greater influence on lowest achievable 2100 temperature levels than on maximum 21st century temperatures (figure S6 available at stacks.iop.org/ERL/8/034033/mmedia). This is because for trajectories with overshoot, the effects of technologies only come to bear in a limited time frame (until the maximum temperature is reached), while in case of 2100 temperatures the effects of technology cumulate over the entire century. This is particularly relevant for bioenergy and CCS, which are ramped up relatively slowly in the 1st half of the century, but become very significant after 2050, if the technologies are available.

4. Discussion and conclusions

In view of the slow progress of international climate negotiations and emissions reduction efforts, the political achievability, and the technological and economic implications of limiting global warming to 2 °C are debated controversially. Model-based scenarios of climate change mitigation pathways are crucial tools for assessing the implications of alternative policy choices. Our work maps out the trade-offs between the stringency of climate targets and economic mitigation challenges at a very high level of detail. It shows how a continuation of ineffective climate policies reduces the option space for future climate policy, increasing mitigation challenges and the reliance on technologies for removing CO_2 from the atmosphere.

Under optimistic assumptions about the outcome of current climate negotiations and technology availability, we estimate that economic mitigation challenges become prohibitively high for temperature stabilization targets below ∼1.7 °C. This means that much of the room to accommodate the 2 °C target has already been consumed. The results suggest that delaying comprehensive emission reductions by

another 15 years pushes this target out of reach. In case of technology limitations, the urgency of reaching a global climate agreement is even higher.

A continuation of weak climate policies inevitably increases the risk of exceeding the 2 °C threshold. Returning to 2 °C in such a scenario will be difficult, and requires large-scale deployment of BECCS. We find that temperature levels reached in 2100 depend to a much higher extent than maximum 2010–2100 temperatures on the availability of technologies, with unavailability of CCS reducing achievable target levels by almost 0.5 °C.

Our research also demonstrates that the effects on short-term consumption growth and energy prices as well as the redistribution of wealth induced by CO_2 pricing are crucial challenges of mitigation pathways consistent with 2 °C. This finding points to potentially strong distributional effects of climate policies, which increase strongly if comprehensive climate policies are delayed further. Additional work is needed to analyze policy instruments and institutional requirements to address these challenges.

The results have important implications for climate policy. They show clear trade-offs between long-term climate targets and economic mitigation challenges. They also demonstrate that these trade-offs depend strongly on the start date of substantial emissions reductions and technology availability. The longer the international community delays the implementation of comprehensive climate policies, the more critical these trade-offs will be.

Acknowledgments

We thank Jan Minx, Nico Bauer, Michael Jakob and Niklas Hoehne for helpful discussions, and Michaja Pehl for his assistance in the data processing. Research for this publication was supported by the German Federal Environment Agency (UBA) under UFOPLAN FKZ 3710 41 135.

References

Azar C, Lindgren K, Obersteiner M, Riahi K, van Vuuren D P, den Elzen K M G J, Möllersten K and Larson E D 2010 The feasibility of low CO_2 concentration targets and the role of bio-energy with carbon capture and storage (BECCS) *Clim. Change* **100** 195–202

Bauer N, Brecha R J and Luderer G 2012 Economics of nuclear power and climate change mitigation policies *Proc. Natl Acad. Sci.* **109** 16805–10

Clarke L, Edmonds J, Krey V, Richels R, Rose S and Tavoni M 2009 International climate policy architectures: overview of the EMF 22 International scenarios *Energy Econ.* 1 **31** 64–81

Edenhofer O *et al* 2010 The economics of low stabilization: model comparison of mitigation strategies and costs *Energy J.* **31** 11–48

Fisher B S, Barrett S, Bohm P, Kuroda M and Mubazi J K E 1996 An economic assessment of policy instruments for combatting climate change *Climate Change 1995: Economic and Social Dimensions of Climate Change. Contribution of Working Group III to the Second Assessment Report of the Intergovernmental Panel on Climate Change* ed P J Bruce, H Lee and E F Haites (Cambridge: Cambridge University Press)

Fisher B S, Nakicenovic N and Hourcade J C 2007 Issues related to mitigation in the long term context *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Inter-governmental Panel on Climate Change* ed B Metz, O R Davidson, P R Bosch, R Dave and L A Meyer (Cambridge: Cambridge University Press)

GEA 2012 *Global Energy Assessment—Toward a Sustainable Future* (Cambridge: Cambridge University Press) (Laxemburg: International Institute for Applied Systems Analysis) (www.globalenergyassessment.org)

Höhne N *et al* 2012 National GHG emissions reduction pledges and 2 °C: comparison of studies *Clim. Policy* **12** 356–77

IEA 2009 *World Energy Outlook* (Paris: International Energy Agency)

IMF 2012 *World Economic Outlook 2012* (Washington, DC: International Monetary Fund) (www.imf.org/external/pubs/ft/weo/2012/02/index.htm)

IPCC 2007 *Climate Change 2007: Synthesis Report. An Assessment of the Intergovernmental Panel on Climate Change* (www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf)

Jakob M, Luderer G, Steckel J, Tavoni M and Monjon S 2012 Time to act now? Assessing the costs of delaying climate measures and benefits of early action *Clim. Change* **114** 79–99

JRC/PBL 2012 *EDGAR Version 4.2 FT2010* (Joint Research Centre of the European Commission/PBL Netherlands Environmental Assessment Agency) (http://edgar.jrc.ec.europa.eu/overview.php?v=42)

Knopf B, Luderer G and Edenhofer O 2011 Exploring the feasibility of low stabilization target *WIREs Clim. Change* **2** 617–26

Koomey J G 2002 From my perspective: avoiding the big mistake in forecasting technology adoption *Technol. Forecast. Soc. Change* **69** 511–8

Kriegler E *et al* 2013 The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies *Clim. Change* submitted

Leimbach M, Bauer N, Baumstark L and Edenhofer O 2009 Mitigation costs in a globalized world: climate policy analysis with REMIND-R *Environ. Model. Assess.* **15** 155–73

Luderer G, Bertram C, Calvin K, De Cian E and Kriegler E 2013 Implications of weak near-term climate policies on long-term climate mitigation pathways *Clim. Change* at press (doi:10.1007/s10584-013-0899-9)

Luderer G, Bosetti V, Jakob M, Leimbach M, Steckel J C, Waisman H and Edenhofer O 2012a The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison *Clim. Change* **114** 9–37

Luderer G, Pietzcker R C, Kriegler E, Haller M and Bauer N 2012b Asia's role in mitigating climate change: a technology and sector specific analysis with ReMIND-R *Energy Econ.* **34** S378–90

Meinshausen M, Meinshausen N, Hare W, Raper S C B, Frieler K, Knutti R, Frame D J and Allen M R 2009 Greenhouse-gas emission targets for limiting global warming to 2 °C *Nature* **458** 1158–62

Meinshausen M, Raper S C B and Wigley T M L 2011 Emulating coupled atmosphere–ocean and carbon cycle models with a simpler model, MAGICC6—Part 1: model description and calibration *Atmos. Chem. Phys.* **11** 1417–56

Peters G P, Andrew R M, Boden T, Canadell J G, Ciais P, Le Quéré C, Marland G, Raupach M R and Wilson C 2013 The challenge to keep global warming below 2 °C *Nature Clim. Change* **3** 4–6

Rogelj J, McCollum D L, O'Neill B C and Riahi K 2013a 2020 emissions levels required to limit warming to below 2 °C *Nature Clim. Change* **3** 405–12

Rogelj J, McCollum D L, Reisinger A, Meinshausen M and Riahi K 2013b Probabilistic cost estimates for climate change mitigation *Nature* **493** 79–83

Rogelj J, Nabel J, Chen C, Hare W, Markmann K, Meinshausen M, Schaeffer M, Macey K and Hohne N 2010 Copenhagen Accord pledges are paltry *Nature* **464** 1126–8

Stocker T F 2012 The closing door of climate targets *Science* **339** 280–2

Tavoni M, De Cian E, Luderer G, Steckel J and Waisman H 2012 The value of technology and of its evolution towards a low carbon economy *Clim. Change* **114** 39–57

UNEP 2012 *The Emissions Gap Report* (www.unep.org/publications/ebooks/emissionsgap2012)

UNFCCC 1992 *United Nations Framework Convention on Climate Change* (www.unfccc.int/resources)

van Vliet J, van den Berg M, Schaeffer M, van Vuuren D, den Elzen M, Hof A, Mendoza Beltran A and Meinshausen M 2012 Copenhagen Accord pledges imply higher costs for staying below 2 °C warming *Clim. Change* **113** 551–61

Wigley T M L and Raper S C B 2001 Interpretation of high projections for global-mean warming *Science* **293** 451–4

Supplementary Information:

Economic mitigation challenges: how further delay closes the door for achieving climate targets

Gunnar Luderer, Robert Pietzcker, Christoph Bertram, Elmar Kriegler, Malte Meinshausen, Ottmar Edenhofer

Contents

1 Methods 1

2 Scenario design 4

3 Economic indicators of the mitigation challenge 7

4 Sensitivity of the results to the implementation of climate policies 11

Supplementary Figures 16

1 Methods

Our analysis combines a state-of-the-art integrated energy-economy-climate model (REMIND) with the probabilistic reduced-form climate model MAGICC. The following sections provide an overview of these modeling frameworks.

1.1 The integrated energy-economy-climate model REMIND

We use version 1.5 of the energy-economy-climate model REMIND to derive greenhouse gas (GHG) emission pathways and policy cost estimates for a large ensemble of mitigation scenarios with different assumptions on technology availability, timing of cooperative action, and carbon price levels under a global cooperative climate policy regime.

A detailed description of REMIND 1.5 is available from (Luderer *et al* 2013b). REMIND is a global model of the energy-economy-climate system spanning the period 2005-2100, with 5-year time steps between 2005 and 2060, and ten year time steps thereafter. The macro-

economic core of REMIND is a Ramsey-type intertemporal general equilibrium model in which global welfare is maximized, as found in similar form in other integrated assessment models such as RICE (Nordhaus and Yang 1996) or MERGE (Manne *et al* 1995). The model computes a unique Pareto-optimal solution which corresponds to the market equilibrium in the absence of non-internalized externalities. The world is divided into 11 regions: there are five individual countries (China, India, Japan, United States of America, and Russia) and six aggregated regions formed by the remaining countries (European Union, Latin America, Sub-Saharan Africa without South Africa, a combined Middle East / North Africa / Central Asia region, Other Asia, Rest of the World). Trade is explicitly represented for final goods, primary energy carriers, and, in case of climate policy, emission allowances. Macro-economic production factors are capital, labor, and final energy. The economic output is available for investments into the macro-economic capital stock as well as for consumption, trade of goods, and financing the energy system.

The macro-economic core and the energy system module are hard-linked via final energy demand and costs incurred by the energy system. Economic activity results in demand for final energy such as transport energy, electricity, and non-electric energy for stationary end-uses. This final energy demand is determined by a production function with constant elasticity of substitution (nested CES production function). The energy system module accounts for endowments of exhaustible primary energy resources (coal, oil, gas and uranium) as well as renewable energy potentials (biomass, hydro power, wind power, solar energy, geothermal energy). REMIND represents capacity stocks of more than 50 technologies for the conversion of primary energy into secondary energy carriers as well as for the distribution of secondary energy carriers to end use sectors. In particular, the model accounts for the possibility of combining fossil fuel and bioenergy use with carbon capture and storage (CCS). Since trees and crops extract CO_2 from the atmosphere, deploying bioenergy in combination with CCS (BECCS) can result in net negative emissions. As shown by the results for technology-constrained scenarios, BECCS technologies are of crucial importance for the achievability of low stabilization targets. Learning-by-doing effects are explicitly represented via learning curves for wind and solar technologies as well as electric vehicles. REMIND does not have any hard limits on the expansion rate of new technologies. In order to mimic real-world inertias in technology up-scaling, a cost penalty ("adjustment costs") is applied that scales with the square of the relative change in capacity investments. This yields technology diffusion rates that are broadly in line with historical patterns (Wilson *et al* 2013). The retirement of fossil capacities before the end of their technological life-times is possible, but limited to a rate of 4% per year.

REMIND calculates energy related non-CO_2 GHG and aerosol emissions via time-dependent emission factors. Emissions from agriculture and land-use are obtained from the land-use model MAgPIE (Lotze-Campen *et al* 2008). Emission reduction potentials of non-energy related CO_2, CH_4 and N_2O emissions are represented via marginal abatement cost curves. Emissions of F-Gases are prescribed exogenously based on RCP data (van Vuuren *et al* 2011a).

REMIND has been used for numerous analyses of the economics of climate change mitigation (Leimbach *et al* 2010a, 2010b, Bauer *et al* 2012a, Lueken *et al* 2011, Bauer *et al* 2012b, Luderer *et al* 2012c). REMIND has also participated in a number of past model inter-comparison exercises (Edenhofer *et al* 2010, Luderer *et al* 2012a, Calvin *et al* 2012), and is currently involved in several on-going inter-comparison exercises.

1.2 The probabilistic climate model MAGICC

To represent uncertainties in the carbon cycle and climate system response to emissions, we employ the reduced complexity climate model MAGICC (version 6) (Wigley and Raper 2001, Meinshausen *et al* 2011c, 2011a). Here, we employ a probabilistic setup of the model. The parameter space has been constrained by historical observations of ocean heat uptake (Domingues *et al* 2008) and surface temperatures over land and ocean in both hemispheres (Brohan *et al* 2006), using a Metropolis Hastings Markov Chain Monte Carlo approach as described in (Meinshausen *et al* 2009). A 600-member ensemble of the resulting joint distribution of the 82-dimensional parameters space has then been drawn, so that the marginal climate sensitivity distribution closely represents the IPCC Fourth Assessment Report conclusions in regard to our uncertainty on climate sensitivity (Rogelj *et al* 2012) . Differently to the setup in (Meinshausen *et al* 2009, Rogelj *et al* 2012), we include a probabilistic permafrost module (Schneider von Deimling *et al* 2012)—thereby accounting for the effect of potential climate feedback from permafrost by additional release of carbon dioxide and methane release from the upper soil compartment. The omission of the permafrost feedback effect has previously been regarded as a research gap (Hatfield-Dodds 2013), although we note that the temperature effect until 2100 is limited.

We consider all important greenhouse gases, tropospheric ozone precursors, the direct and indirect aerosol effects and landuse albedo. CO_2, CH_4, N_2O, sulfur, black carbon and organic carbon emissions are endogenous results from the REMIND model, while other forcing components are complemented from corresponding RCP emission scenarios (van Vuuren *et al* 2011a, 2011b, Masui *et al* 2011). For emissions of ozone depleting substances we assume

the WMO2006 emissions scenario – consistent with the setup for creating the RCP GHG concentration profiles (Meinshausen *et al* 2011b).

2 Scenario design

Our analysis is based on a large set of climate mitigation scenarios compiled along the dimensions of (i) timing of global cooperative mitigation action, (ii) availability of low carbon technologies, and (iii) stringency of long-term climate policies, controlled by different globally harmonized carbon price levels. The combination of these dimensions yields a scenario ensemble of 285 different REMIND runs, each representing one energy-economic development pathway. For each scenario, the GHG emission trajectories resulting from REMIND were used to calculate 600 climate realizations with the probabilistic climate model *MAGICC*, yielding a total of 171'000 climate model simulations. The variations along the different scenario dimensions are presented and motivated in the following.

2.1 Timing of climate policy

In the long-term, any climate stabilization target requires near-zero emission levels. As a consequence, climate policy will only be successful if it eventually establishes a comprehensive climate regime that covers virtually all countries and emitting sectors. The second scenario dimension explores delay in setting up such a global comprehensive climate policy regime. The specifications of the delayed-action scenarios follow those of the RoSE study (Luderer *et al* 2013a).

P0. Weak-policy baseline (WeakPol)

This scenario is designed as a reference scenario that includes weak climate policies. It is meant to represent the unambitious end of short- and long-term climate policy developments. It was constructed by considering existing climate policies, a weak interpretation of the 2020 Copenhagen Pledges, and an extrapolation of these targets beyond 2020 based on emissions intensity (GHG emissions per unit of GDP). Three country groups are considered: industrialized countries (Group I), developing countries excluding resource exporters (Group II), and fossil resource exporters of the former Soviet Union and Middle East (Group III). Climate policy is assumed to remain fragmented, with no emissions trading between regions until 2020. Limited trading of emissions between industrialized and developing countries is allowed after 2020. It is assumed that resource-exporting countries (Group III) will not adopt any binding targets. Furthermore, it is assumed that land-use

emissions will not be subject to carbon pricing. A detailed description of the *WeakPol* scenario is provided in Section SI 6. The assumptions of the *WeakPol* scenarios with regard to regional emission reduction targets are identical to those used in Luderer et al. (2013).

P1. Weak and Fragmented climate policy until 2015 (Frag2015)

The *Frag2015* scenario considers the most optimistic possible outcome of the current climate negotiation process and the Durban Platform. It assumes that a global climate agreement is reached by 2015, and that comprehensive emission reductions are implemented from 2020 onwards. Until 2015, the model follows the weak policy scenario, without anticipating more stringent future climate policies. Starting with the 2020 model time step, a global cooperative climate regime is implemented with comprehensive regional and sectoral coverage.

P2. Weak and Fragmented climate policy until 2020 (Frag2020)

The *Frag2020* scenario considers a somewhat more pessimistic outcome of the Durban Platform, assuming that it fails to deliver 2020 emission reductions beyond those of the current pledges as implemented in the *WeakPol* scenario, and that the implementation of comprehensive global emissions reductions is delayed until 2025.

P3. Weak and Fragmented climate policy until 2030 (Frag2030)

The *Frag2030* scenario assumes a failure of the Durban Platform negotiations, resulting in unambitious and fragmented climate policies following the *WeakPol* scenario without anticipating more stringent future climate policies until 2030. Comprehensive global emissions reductions start in 2035.

P4. Immediate action (Immediate)

In the immediate action scenario we assume that global cooperative climate mitigation policies start immediately, with global comprehensive emission reductions starting in the 2015 model time step. It must be considered hypothetical, since none of the current climate negotiation tracks would be able to deliver such an outcome.

2.2 Technology availability

Earlier studies (Azar *et al* 2010, Edenhofer *et al* 2010, Tavoni *et al* 2012) have shown the crucial importance of low-carbon technologies for costs and achievability of low stabilization targets. To further explore the influence of technology availability on the lower limit of achievable climate targets, we produced seven scenario sets with different idealized

assumptions on technology availability. With the exception of the the *NoBECCS* case, the scenario specifications are identical to those used in the EMF27 study (Kriegler *et al* 2013):

T1. Full technology portfolio (Default)

All technologies represented in the REMIND model are assumed to be available. Default assumptions regarding final energy demand are implemented, with autonomous energy intensity improvements (AEII, i.e., reductions in final energy demand per unit of GDP in absence of climate policy) in line with the historical rate of about 1.2%/yr. Bioenergy use is limited to 300 EJ/yr.

T2. No carbon capture and storage (NoCCS)

All conversion technologies with carbon capture and storage, both with fossil fuels or bioenergy as feed-stocks, are excluded from the mitigation portfolio. This scenario setting is motivated by the slow progress in up-scaling CCS to commercial scale, potential environmental impacts and limited public acceptance of geological storage in some countries, as well as institutional barriers.

T3. No bioenergy combined with carbon capture and storage (NoBECCS)

All technologies that combine bioenergy use with carbon capture and storage are excluded from the mitigation portfolio. Specific challenges applying to BECCS in addition to those of CCS include (a) the lower technological maturity of BECCS technologies, (b) sustainability constraints to bioenergy production (see LowBio case), (c) institutional challenges related to incentivizing negative emissions.

T4. Low bioenergy availability (LimBio)

The global bioenergy potential is limited to 100 EJ. This scenario is motivated by a variety of concerns about the sustainability of large-scale bioenergy production regarding (a) scarcity of arable land, (b) potential freshwater demand for irrigation, (c) effect on food prices, (d) potential indirect land-use change emissions (ILUC) induced by bioenergy production, and (e) potential loss of biodiversity.

T5. Nuclear phase-out (NucPO)

No nuclear capacity additions beyond those currently under construction. This scenario is motivated by limited public acceptance of nuclear power in view of (a) security concerns in the aftermath of the Fukushima accident, (b) challenges related to nuclear waste disposal, and (c) proliferation concerns.

T6. Limited Wind and Solar Power (LimSW)

The share of electricity production from wind and solar power is limited to 20% of total electricity in each region. This scenario is motivated by the challenges related to the fluctuating supply from variable renewable energy sources.

T7. Low energy intensity (LowEI)

This set of scenarios assumes autonomous energy intensity improvements that are higher than those in the *Default* scenario, and exceed those observed historically. Baseline energy intensity is 25% lower than in *Default* in 2050, and 40% lower than in *Default* in 2100. The *LowEI* scenarios describe a world in which behavioral changes result in lower demand for final energy, and barriers for energy efficiency improvements are decreased.

2.3 Carbon price levels

We explore the effect of long-term climate policy stringency on climate stabilization levels and mitigation costs by varying the uniform carbon price signal applied in the global cooperative climate regime. We use 2020 reference carbon price levels of 5, 10, 20, 30, 40, 50, 100, 200 and 500 US$2005/t$CO_2$. Since the model's responsiveness to carbon pricing is highest at low to medium prices, we chose to use more narrowly spaced price steps below 50 US$2005/t CO_2. By default, we assume carbon prices to increase by 5% per year. This rate is very close to the model-endogenous discount rate, thus implying inter-temporal efficiency in minimizing cumulated GHG emissions. Section SI 4 explores the sensitivity of the results to the development of carbon prices over time.

We derived emission prices for non-CO_2 Kyoto gases based on global warming potentials from the IPCC AR4. We also calculate *Baseline* scenarios without any climate policies as a baseline for measuring the effect of mitigation.

3 Economic indicators of the mitigation challenge

For the analysis, we derived four indicators as proxies for the potential economic and political challenges associated with the implementation of climate policies: (i) aggregated mitigation costs as a measure for costs in the long run, (ii) transitional consumption growth reduction as a proxy of short-term economic effects, (iii) the aggregated carbon trade volume as a proxy for potential distributional conflicts under an international cap-and-trade system, and (iv) transitory energy price increases during the phase-in of comprehensive climate policies. They are defined and motivated in the following.

3.1 Aggregated mitigation costs (AMC)

Aggregate mitigation costs quantify the inter-intertemporally aggregated impact of climate mitigation policies on affluence. They are commonly used for characterizing long-term mitigation scenarios (B.S. Fisher *et al* 2007, Edenhofer *et al* 2010, Luderer *et al* 2012a). We calculate them as aggregated discounted consumption losses expressed relative to aggregated, discounted gross world product GWP in the baseline:

$$AMC = \left(\sum_{t=2010}^{2100} (C_{Baseline} - C_{Pol}) \cdot (1+\delta)^{2010-t} \right) \Big/ \left(\sum_{t=2010}^{2100} GWP_{Baseline} \cdot (1+\delta)^{2010-t} \right) \cdot 100\%,$$

where C denotes consumption, and a discount rate $\boldsymbol{\delta}$ of 5% p.a. is used. While aggregated mitigation costs typically only amount to a few percent of cumulative economic output, they can be very significant in absolute terms. For the REMIND GWP baseline used here, each % of cumulative costs corresponds to discounted aggregated costs of US$ 19.6 tn in values of 2010. We use reference mitigation cost values of 2% and 4% of GWP for the analysis of climate target achievability. This can be compared to the target to devote 0.7% of the gross national product (GNP) of OECD countries to Official Development Assistance (ODA) (United Nations 2002).

3.2 Transitional growth reduction (TGR)

Economic losses occurring during the transition from a regime without climate policy to a regime with stringent climate policies are a crucial barrier to the implementation of climate policies. We define the transitional growth reduction as the maximum of the difference between decadal consumption growth rate in the baseline and in the policy scenario, in units of percentage points [pp]:

$$TGR = \max_{2010<t<2050} \left(g_{Baseline}(t) - g_{Pol}(t) \right),$$

where for each scenario

$$g(t) = \left(C(t+5\text{a}) - C(t-5\text{a}) \right) / C(t) \cdot 100\ \%$$

is the decadal rate of consumption growth in units of %.

In the baseline, i.e., without climate policies, globally aggregated consumption grows at a rate of around 30-40 % per decade in the first half of the 21st century. The transition from a weak, fragmented climate policy regime to a regime with stringent and comprehensive emission reductions can slow consumption growth markedly. The timing of climate policy has

important implications for the incidence of mitigation costs over time (see Figure 3 in the main paper). In case of immediate action, costs for reaching the 2°C target with a high likelihood are well below 1% of gross world product (GWP) in 2020 and increase gradually over time. For the scenarios with delayed cooperative action, the picture looks different: As the weak policies only have a small effect on the economy, near-term costs in the delayed scenarios with delayed cooperative action are rather small. Once a stringent global climate regime is implemented, however, costs increase to levels that exceed those in the immediate scenario reaching the same long-term target.

In some extreme scenarios, the transition from the weak, fragmented climate policy regime to stringent climate policies can therefore result in transitory mitigation costs of 10pp or higher. Such dramatic short-term effects render the political feasibility of such pathways questionable. For comparison, based on the IMF data (IMF 2012) the financial crisis of 2008 can be estimated to have reduced global economic output by around 5%. Another study estimated the effect on the economies of the US and Europe to be of similar magnitude (Gros and Alcidi 2010). For the purpose of this study, we use a reference range of 2.5-5 pp to examine how climate policy induced consumption growth reductions limit economically achievable climate targets.

3.3 Energy price increases (EPX)

Energy price increases are among the most direct impacts of climate policies on households and firms. The impact of high energy prices will depend on the rates of price increases: if energy prices rise quickly, there is little time for adaptation through technological or behavioral changes.

To examine the effect of climate policies on energy prices, we derive a global final energy price index recursively, by calculating the market value of the final energy demand basket at time t relative to the price the same final energy basket would have cost one period, i.e., 5 years, earlier:

$$EPX(t) = EPX(t - 5a) \cdot \sum_r \sum_i p_{i,r}(t)\, FE_{i,r}(t) \Big/ \sum_r \sum_i p_{i,r}(t - 5a)\, FE_{i,r}(t)$$

where $p_{i,r}$, $FE_{i,r}$ are the demands and prices of final energy carrier *i* in region *r,* respectively, and *EPX(*2010*)* is set to unity for normalization. This method is akin to the calculation of a chained consumer price index. The decadal growth rate of the energy price index can be readily calculated as

$$g_{EPX}(t) = (EPX(t + 5\text{ a}) - EPX(t - 5\text{ a}))/\, EPX(t) \cdot 100\ \%$$

The maximum climate-policy-induced short-term energy price increase, in units of percentage points [pp] follows as

$$EPI = \max_{2010<t<2050} \left(g_{EPX,BaU}(t) - g_{EPX,Pol}(t)\right).$$

Figure S1a shows the development of the global energy price index over time. Energy prices would increase by a rate of roughly 20% per decade even if no climate policies were implemented, reflecting increasing global energy demand and a gradual depletion of fossil resources. Climate policy adds to this. In the *Frag2015* scenario and under *Default* technology assumptions, reaching the 2°C target implies a maximum additional energy price increase of around 20 pp in the decade following the implementation of the mitigation target. A further delay of a cooperative agreement results in much stronger short-term price increases of up to 100 pp in *Frag2030* (Figure 2d in the main paper).

Recently, substantial price increases have occurred in various industrialized countries, such as a 60% price increase in household electricity prices in Germany between 2000 and 2010, or a more than 100% price increase for gasoline in the US between 1998 and 2008 (ENERDATA 2013). For developing countries, there is some evidence that increases in energy prices can be causes of social unrest (Morgan 2008). For instance, a 70% increase of gasoline prices and a trebling of electricity prices (albeit in a much shorter time frame than a decade) were an important trigger for riots that occurred in Indonesia in 2008 (Purdey 2006). This leads us to assume that critical levels of transitional, climate-policy-induced energy price increases might be in the range of 50-100 pp.

3.4 Carbon market value (CMV)

Not only aggregated costs, but also distributional effects of climate policy matter. In order for climate policies to be efficient, carbon prices need to be harmonized across regions and sectors, so as to ensure equal mitigation costs at the margin (Stern 2007). While carbon pricing results in costs for emitters, it also produces potentially large revenues, for instance for the government in case of a carbon tax or full auctioning of emission permits in the context of an emissions trading scheme. Similarly, in the context of an international emissions trading scheme, the allocation of the permissible emissions budget across individual countries determines capital flows induced by emissions trading, and therefore has strong distributional implications (Lueken *et al* 2011, Luderer *et al* 2012b). We therefore use the cumulated carbon market value as an indicator of the institutional challenges to manage

distributional conflicts arising from emissions trading both on the national and international level, and define it as

$$CMV = \sum_{t=2010}^{2100} p_{CO2}(t) \cdot E(t) \cdot (1+\delta)^{2010-t}$$

where E refers to all positive greenhouse gas emissions, but excludes negative emissions from BECCS, and $p_{CO2}(t)$ is the price of CO_2.

The carbon market value as a function of temperature levels is quite sensitive to timing of mitigation action and technology availability. In the *Frag2015* scenario, reaching the 2°C target with a cap-and-trade regime that covers all regions and sectors implies an aggregated carbon market value of about US$ 56 tn in values of 2010 (Figure 2c). The aggregated market value of fossil fuels consumed in a baseline scenario without climate policy is similar in magnitude, with oil accounting for US$ 46 tn, and coal, oil and gas combined for US$ 83 tn in values of 2010. We therefore assume that critical levels for the inter-temporally aggregated carbon market value might be in the range of US$2010 50-100 tn.

4 Sensitivity of aggregated mitigation costs to the discount rate

Since mitigation costs as a share of GWP are not constant over time (Figure 3b of the main paper), aggregated mitigation depend indeed on the discount rate used for the inter-temporal aggregation. To ensure consistency with the investment dynamics of the model, a discount rate of 5% p.a. was used for the calculation of the aggregated mitigation costs, which is in good agreement with the interest rate that emerges endogenously in the model (and historically observed rates of return on equity, see (Gollier 2012)). From the perspective of a representative household, the discount rate depends on two other ethical parameters, rate of pure time preference and the elasticity of marginal utility (Ramsey 1928). Alternative choices of these parameters can result in either lower or higher social discount rates. In the aftermath of the Stern Review (Stern 2007), a fierce debate about the appropriate use of discount rates in the economics of climate change emerged (Nordhaus 2007, Mendelsohn *et al* 2008, Weitzman 2007, Dasgupta 2006, Dietz and Stern 2008). Figure S4 shows a sensitivity study of aggregated mitigation costs for discount rates of 2.5%, 5% and 7.5% p.a. We find that a lower discount rate results in a higher aggregated costs indicator (since it puts more weight to the long-term costs, which are higher as a share of GWP) and a stronger economic penalties of delayed action.

5 Sensitivity of the results to the implementation of climate policies

We implemented long-term mitigation policies in terms of exponentially increasing carbon price pathways (cf. Section SI 2). In principle, other approaches are conceivable for representing climate policies in the model. Here we show that the approach taken represents close-to-optimal climate policies, and therefore allows us to explore the efficient frontier in the trade-off between climate targets and economic costs. The optimal pricing over time of the limited remaining atmospheric carbon budget implied by a given climate target (Meinshausen *et al* 2009, Matthews *et al* 2009) is directly related to the economics of exhaustible resources, and is therefore akin to the optimal pricing of coal, oil and gas. Therefore, the Hotelling-rule (Hotelling 1931) can be applied. According to this rule, an inter-temporally optimal abatement strategy implies that carbon prices increases at the discount rate, in order to fulfill the intertemporal arbitrage condition determining the optimal use of the imposed carbon budget over time. The rate of increase of 5% p.a. that we assumed in our policy scenarios is close to the discount rate that emerges endogenously in REMIND, which is around 5-6 p.a. Therefore, a scenario experiment with an inter-temporal GHG emissions budget yields results that are very similar to those obtained from carbon price scenarios with comparable stringency (Figure S4).

There is no perfect correlation between the GHG emission budget and maximal 21st century temperature increases, especially in the case of delayed action scenarios with overshooting temperatures. We therefore explore the effect of implementing climate policy in terms of explicit not-to-exceed temperature targets. This allows the model to exploit flexibilities in adjusting the development of price ratios between long-lived and short-lived greenhouse gases over time and across different greenhouse gases (Manne and Richels 2001). We observe that the resulting aggregated mitigation costs implied by a certain maximum 21st century temperature are only marginally below the achievability frontier derived based on exponentially increasing carbon prices with global warming potentials (Figure S4a). On the other hand, the implementation in terms of explicit not-to-exceed temperature targets results in significantly higher costs as a function of 2100 temperature levels for temperature targets lower than 2°C. The reason for this is that a stringent GHG tax/budget scenario leads to temperature overshooting in the 21st century, while a not-to-exceed temperature target creates no incentive to reduce temperatures below the maximum temperature reached around 2040-2080, even if such a reduction might be achieved at comparatively low cost (Figure S3b).

Finally, we examined if a slower phase-in of the carbon tax during the transition from weak to comprehensive climate policies can alleviate the economic shocks observed in delayed-action scenarios with stringent long-term targets. To this end, we ran *Frag2030* scenarios with a more gradual ramp-up of CO_2 price levels from ~30% of the reference price value in 2035 to the full reference price value in 2060. For these scenarios we found that the increase of maximum temperature counteracts the benefit in terms of lower economic challenges, both in terms of aggregated mitigation costs, and in terms of transitional consumption growth reductions. As a consequence these scenarios are in line with or above the achievability frontier constructed from the default price paths with exponentially increasing price levels.

6 Weak policy scenario

This section provides a detailed description of the weak policy scenario that we introduced as a reference point for the scenarios with a delay in global cooperative mitigation action. It is meant to represent the unambitious end of realistic short and long-term climate policy developments. It was constructed by considering existing climate policies, a weak interpretation of the 2020 Copenhagen Pledges applied to emissions from fossil fuels and industry, and an extrapolation of these targets beyond 2020 based on emissions intensity (GHG emissions per unit of GDP).

We consider three country groups: A group of industrialized countries (Group I, roughly corresponding to the OECD), developing countries without resource exporters (Group II), and fossil resource exporters (Former Soviet Union and Middle East, Group III). Climate policy is assumed to remain fragmented, with no emissions trading between regions until 2020. Limited emissions trading between industrialized and developing countries is allowed after 2020. Under *Default* technology assumptions, the *WeakPol* scenario results in 2020 greenhouse gas emission levels of 57.5 Gt CO_2e, consistent with the emissions estimate obtained in the latest UNEP gap report for the unconditional pledges under lenient rules(UNEP 2012). The specific assumptions for the eleven REMIND regions are described in the following.

Emission targets for industrialized countries (Group I)

For Group I countries, 2020 emission reduction targets are formulated relative to a base year (either 1990 or 2005). Unconditional emission reduction pledges were used where available. If a range for reduction targets is given, we used the lower end (weak interpretation) of pledges. Current long-term (2050) reduction ambitions are assumed to be watered down.

EU-27: 2020 ambition on the low end of its Copenhagen Pledges: 20% below 1990. This corresponds to a 13% reduction relative to 2005. Further, we assume that the 2050 emission reduction target is watered down to 40%, and 2100 reductions reach 80%, relative to 1990, respectively.

USA: The target to reduce emissions 17% below 2005 in 2020 is assumed not to materialize. Instead, we assume no emission reductions beyond those achieved in the baseline levels. Because of increasing use of natural gas results, baseline emissions in 2020 are 8% below 2005 levels. After 2020, the emissions cap is assumed to decrease by 0.5% per year in the period 2020-50, and 1% per year after 2050.

Japan: The 25% emission reduction pledge relative to 1990 is conditional, and therefore assumed not to materialize. Instead, we assumed a 10% emission reduction relative to 1990 by 2020, and a 40% reduction until 2050.

Rest of the World: The "Rest -of the World" region, largely composed of other states of the "Umbrella Group" (Canada, Australia, New Zealand), plus South Africa, are assumed to achieve combined 2020 emission reductions of 5% relative to 2005. Further, emissions are assumed to decrease by 0.5% per year in the period 2020-50, and 1% per year after 2050.

Emission targets for emerging economies and developing countries, excluding oil exporting countries

Developing countries have formulated their 2020 pledges in terms of (a) emissions reductions relative to baseline, or (b) reductions in carbon emission intensity of GDP relative to a base year. In absence of concrete pledges beyond 2020, we assumed yearly emission intensity improvements comparable to those implied by the 2020 pledges.

China: China pledged to "lower its carbon dioxide emissions per unit of GDP by 40-45% by 2020 compared to the 2005 level, increase the share of non-fossil fuels in primary energy consumption to around 15% by 2020 and increase forest coverage by 40 million hectares and forest stock volume by 1.3 billion cubic meters by 2020 from the 2005 levels." China is currently putting in place domestic measures to fulfill this pledge. We therefore assume that it fulfills the ambitious end of the pledge (-45%) for 2020. After 2020, China is assumed to continue to decrease the emissions per unit of GDP by 3% per year.

India: India pledged to "reduce the emission intensity of its GDP by 20 to 25% by 2020 in comparison to the 2005 level." In the REMIND scenarios, this target is not binding. We assume that India follows China in reducing emissions per unit of GDP by 3% per year after 2020.

Other Asia: Several other Asian countries have pledged substantial emission reductions relative to baseline—most notably, South Korea (30% relative to baseline) and Indonesia (26% relative to baseline). As a group, we assume other Asian countries to deliver emission reductions of -20% relative to baseline by 2020. After 2020, they are decrease the emissions per unit of GDP by 3% per year, equal to the decarbonization rate assumed for China.

Latin America: Several other Latin American countries have pledged substantial emission reductions relative to baseline—most notably the Brazil (36% below baseline) and Mexico (30% baseline), which account for a substantial share of Latin American emission. We assume that Latin America as a group will deliver 15% emission reduction from non-LUCF emissions. We further assume that LAM will reduce emission intensity by 2.5% per year in 2020-2050, and by 3% per year after 2050.

Sub-Saharan Africa (excl. South Africa) : Sub-Saharan Africa is assumed not to take any targets before 2020. After 2020-50, a reduction target of emission intensity per unit GDP of 2.5% per year is prescribed. However, this target is not binding, since economic growth exceeds emissions growth by more than 2.5% per year. After 2050, a target on the reduction of emission intensity per unit GDP of 3.5% per year is assumed.

Emission targets for resource exporters

The resource exporting REMIND regions (Middle East / North Africa / Central Asia and Russia) are assumed not to have an incentive to take any binding target. Countries of the Middle East have not pledged any emission reduction targets. Russia's unconditional target of -15 below 1990 is well above projected baseline emissions. Carbon leakage, i.e. higher emissions compared to baseline in Group III countries in response to climate policies in Group I and II countries is allowed.

Emission control in Sectors

We assume all Kyoto-Gas Emissions excluding land use, land use change and forestry (LULUCF) to be included in the reduction targets and subject to climate policies. Given higher institutional requirements for monitoring and reporting of land-use related CO_2 emissions, we assume climate policies to be ineffective in controlling LULUCF emissions. LULUCF emissions are thus assumed not to be subject to carbon pricing, and are not included in the emission reduction targets.

International Emissions Trading

In the Weak Policy Scenario, we assume global carbon markets to remain fragmented. Specifically, the following rules for the trade of emission allowances and intertemporal flexibility in the mitigation effort were assumed to apply:

- No emissions trading, nor banking or borrowing is permitted until 2020
- After 2020, unrestricted emissions trading between members of Group I
- After 2020, unrestricted emissions trading between members of Group II
- The total net import of Group I (from Group II) is restricted to 20% of the combined mitigation requirement of Group I (i.e., the difference between baseline emissions and emission allowances under the cap).
- Full when-flexibility is allowed within the periods 2020-2050 and 2050-2100.
- Excess emission allowances from 2020-2050 can be banked to the 2050-2100 period, but no borrowing from the second period is allowed in the first period.

Supplementary Figures

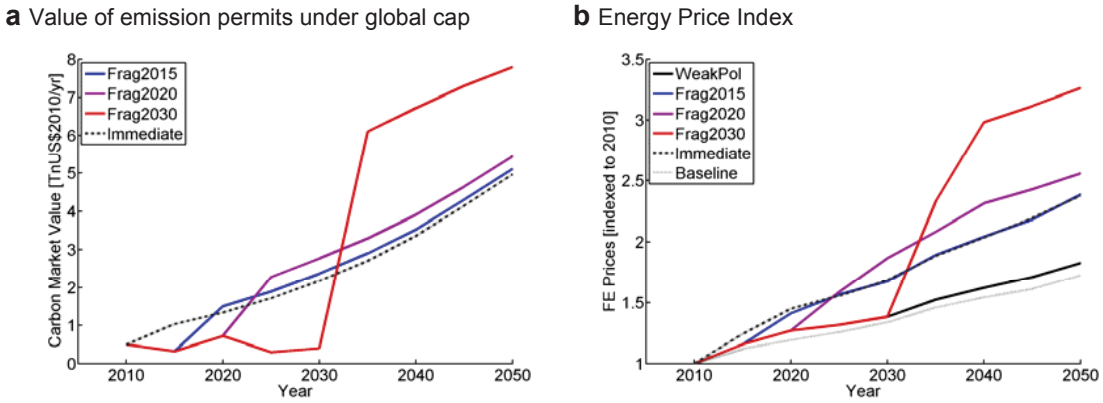


Figure S1: Effect of different near-term climate policy regimes on the development of (a) the value of emission permits under the global cap over time, and (b) the global energy price index. For the mitigation scenarios *Immediate, Frag2015, Act2030* and *Frag2030* cumulative emissions budget of 2500 $GtCO_2e$ were considered.

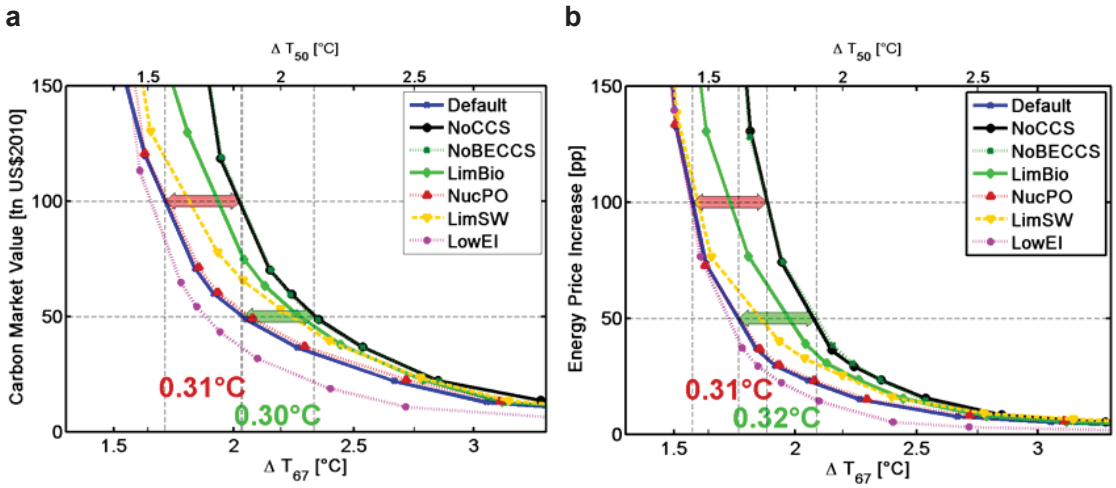


Figure S2: Temperature-cost-tradeoff curves showing the effect the technology availability on (a) carbon market value, and (b) energy price increase (*Frag2015* scenario). Temperature targets (maximum 2010-2100 temperatures) reached with a 67% likelihood (lower axis) or 50% likelihood (upper axis) are shown. Numbers indicate shift in terms of ΔT_{67}.

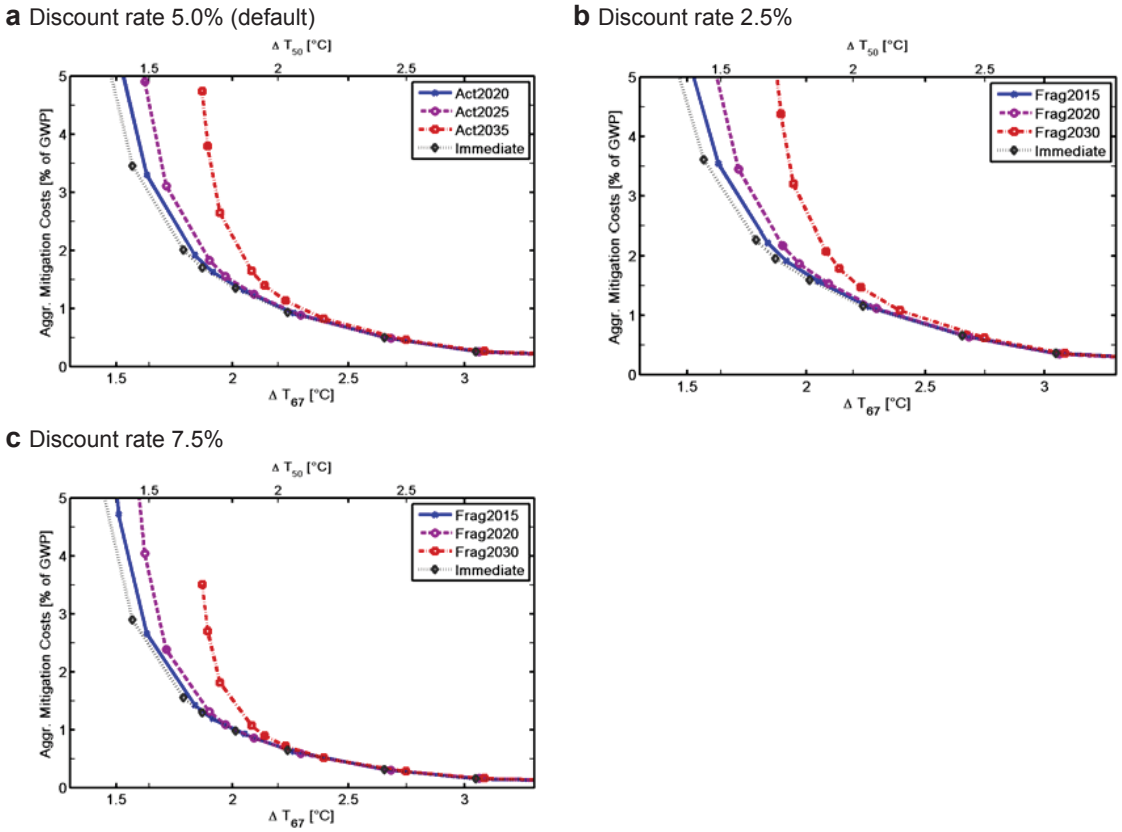


Figure S3: The sensitivity of aggregated mitigation costs to the choice of discount rate in the inter-temporal aggregation (cf. Fig. 2a of the main paper).

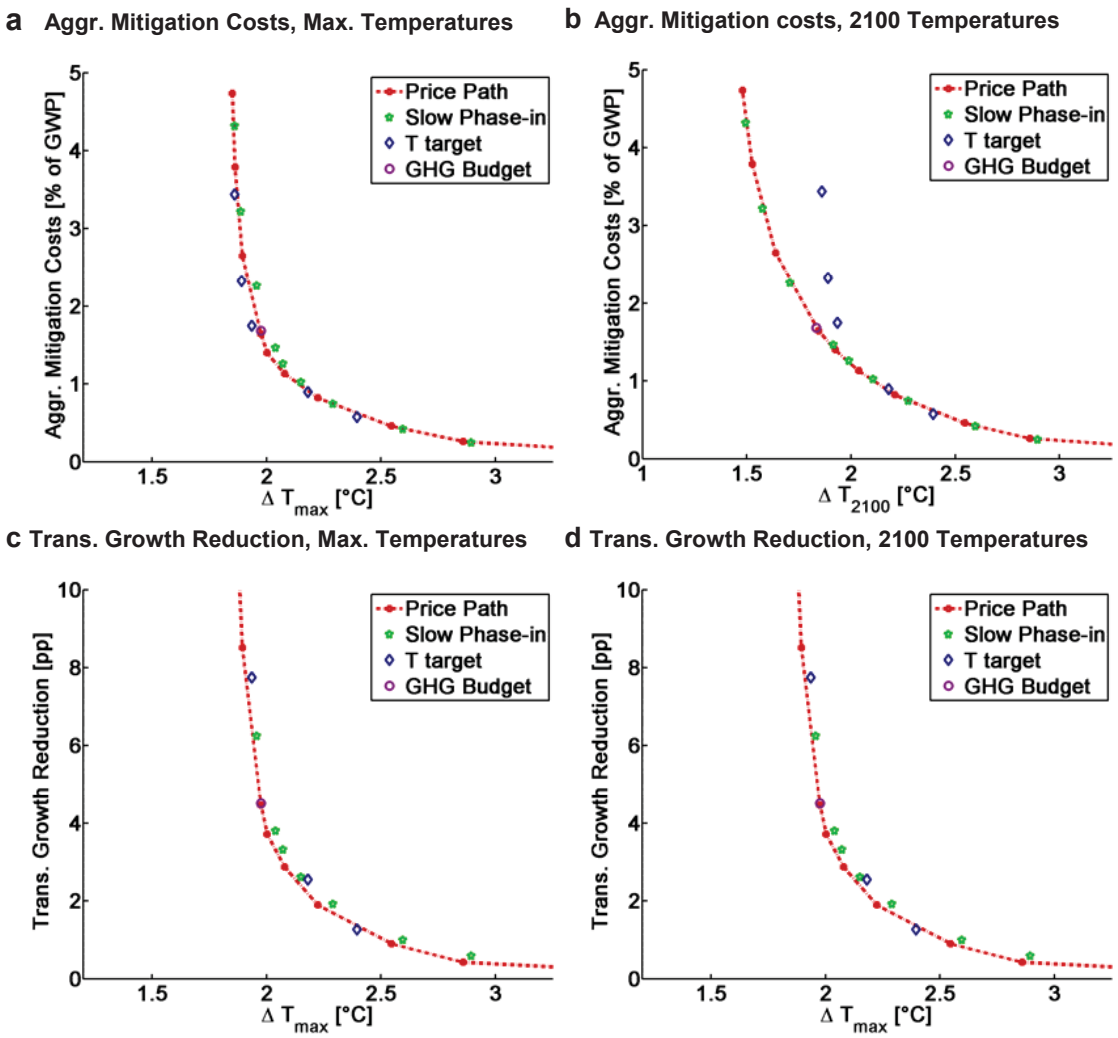


Figure S4: The effect of different climate target implementations examined for the example the *Frag2030* scenario with *Default* technology assumptions. In addition to exponential carbon price pathways (which are used for the analysis in the main paper), we show a scenario with a pre-scribed 2010-2100 GHG emission budget (purple circle), an explicit not-to-exceed temperature target (blue diamonds), and price paths with a slower phase-in of carbon prices. The results show that the temperature-cost trade-off curves derived based on exponential price paths are a robust indicator of the efficient achievability frontier for a given scenario setup.

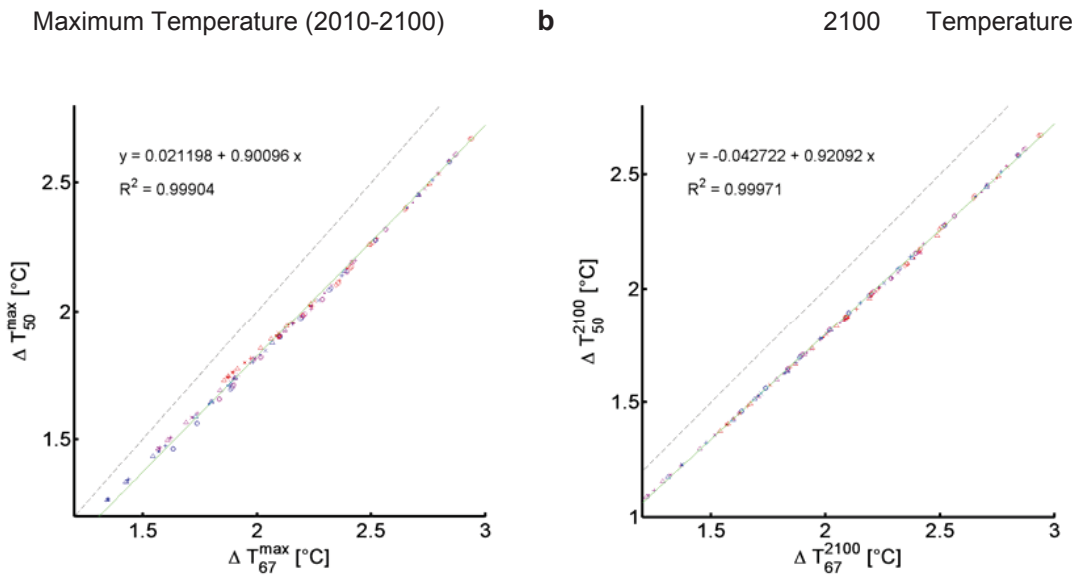
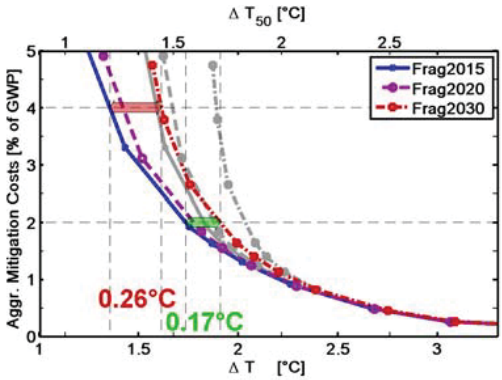
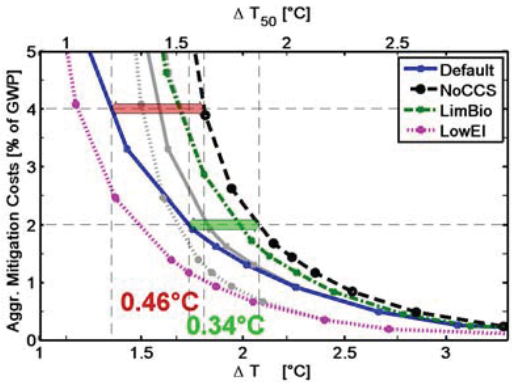


Figure S5: Correlation between temperature increases not exceeded with 67% and 50% likelihood for (a) maximum 2000-2100 temperatures, and (b) 2100 temperatures. Each individual data point corresponds to one climate mitigation scenario, with different colors indicating different assumptions along the delay dimension, and different markers correspond to different technology assumptions.

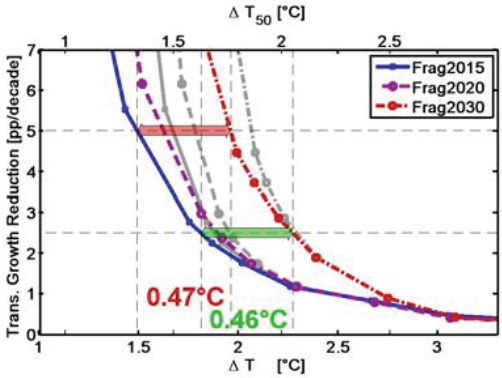
a Effect of timing on AMC *(Default* tech)



b Effect of technology on AMC *(Frag2015)*



c Effect of timing on TGR *(Default* tech)



d Effect of Technology on energy prices

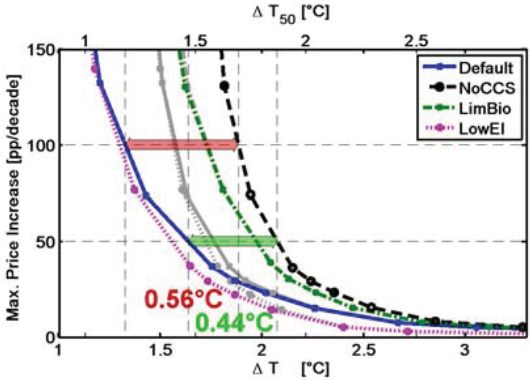


Figure S6: Temperature-cost tradeoff curves considering 2100 temperature levels. Grey lines indicate corresponding trade-off curves that consider maximal 2000-2100 temperatures. The left column shows the effect of mitigation timing, the right column the effect of technology availability. (a), (b) show aggregated mitigation costs, (c) shows transitional growth reductions, and (d) shows the maximum climate-policy induced decadal energy price increase. Note that for the *NoCCS* and *LimBio* scenarios, maximal temperatures are reached in 2100, therefore colored lines (2100 temperature) lie on top of the grey lines (maximal 21st century temperature).

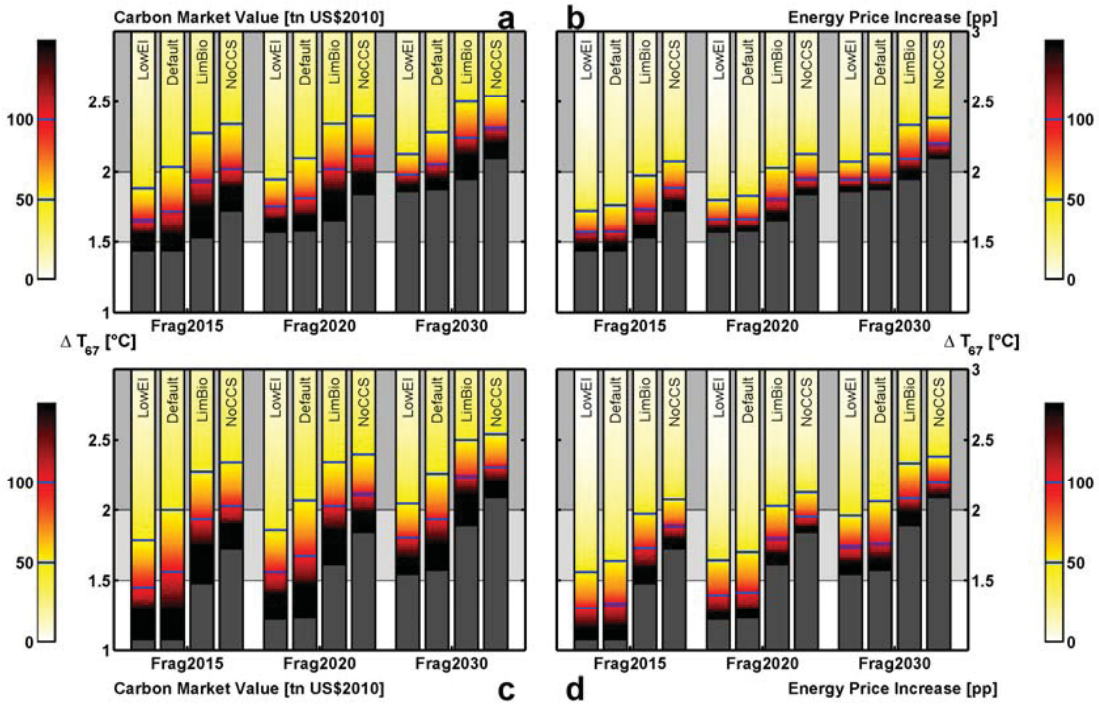


Figure S7: Overview of the combined effects of mitigation timing and technology availability on achievability of not-to-exceed targets and 2100 temperature target that allow for temporary overshoot. Graphs show economic challenges (color shading) in terms of aggregated carbon market value (left panels a,c), and short-term energy price increase (right panels b,d), as a function maximal 2010-2100 temperature increase (upper panels) or 2100 temperature increase (lower panel). Dark grey areas at the base of bars indicate temperature target levels that were not achieved with the range of carbon price paths assumed.

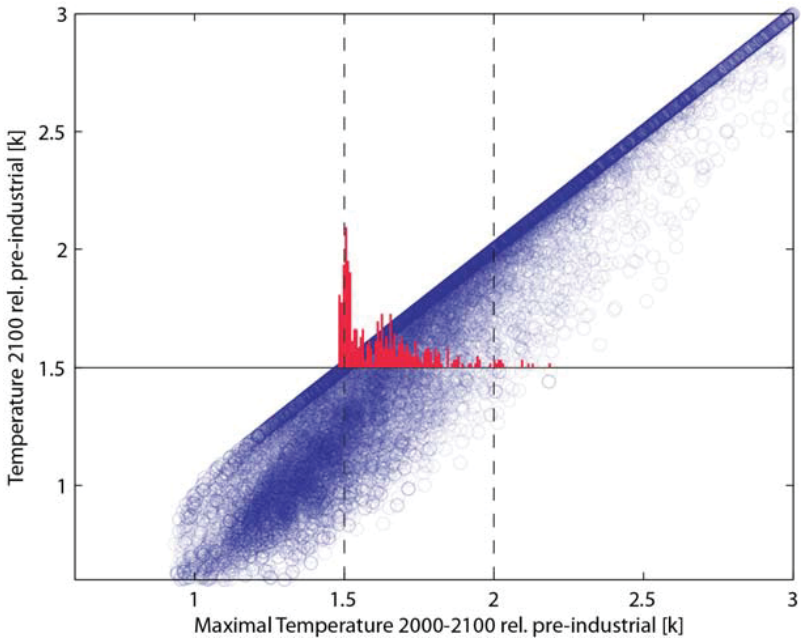


Figure S8: Relationship between maximum surface air temperatures during the 21st century (horizontal axis) and 2100 surface air temperatures (vertical axis) for the full set of 171,000 climate model realizations of the 285 REMIND scenarios. The red histogram shows the distribution of maximal 2000-2100 temperatures that result in a temperature of 1.5°C in 2100.

References

Azar C, Lindgren K, Obersteiner M, Riahi K, Vuuren D P van, Elzen K M G J den, Möllersten K and Larson E D 2010 The feasibility of low CO2 concentration targets and the role of bio-energy with carbon capture and storage (BECCS) *Climatic Change* **100** 195–202

B.S. Fisher, Nakicenovic N and Hourcade J C 2007 Issues related to mitigation in the long term context *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Inter-governmental Panel on Climate Change* ed B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (Cambridge University Press, Cambridge)

Bauer N, Baumstark L and Leimbach M 2012a The REMIND-R model: the role of renewables in the low-carbon transformation—first-best vs. second-best worlds *Climatic Change* **114** 145–68

Bauer N, Brecha R J and Luderer G 2012b Economics of nuclear power and climate change mitigation policies *PNAS* **109** 16805–10

Brohan P, Kennedy J J, Harris I, Tett S F B and Jones P D 2006 Uncertainty estimates in regional and global observed temperature changes: A new data set from 1850 *Journal of Geophysical Research: Atmospheres* **111** n/a–n/a

Calvin K, Clarke L, Krey V, Blanford G, Jiang K, Kainuma M, Kriegler E, Luderer G and Shukla P R 2012 The role of Asia in mitigating climate change: Results from the Asia modeling exercise *Energy Economics* **34, Supplement 3** S251–S260

Dasgupta P 2006 Comments on the Stern Review's economics of climate change *University of Cambridge* Online: http://econ.tau.ac.il/papers/research/Partha%20Dasgupta%20on%20Stern%20Review.pdf

Dietz S and Stern N 2008 Why economic analysis supports strong action on climate change: a response to the Stern Review's critics *Review of Environmental Economics and Policy* **2** 94–113

Domingues C M, Church J A, White N J, Gleckler P J, Wijffels S E, Barker P M and Dunn J R 2008 Improved estimates of upper-ocean warming and multi-decadal sea-level rise *Nature* **453** 1090–3

Edenhofer O, Knopf B, Barker T, Baumstark L, Bellevrat E, Château B, Criqui P, Isaac M, Kitous A, Kypreos S, Leimbach M, Lessmann K, Magné B, Scrieciu S, Turton H and van Vuuren D P 2010 The Economics of Low Stabilization: Model Comparison of Mitigation Strategies and Costs *The Energy Journal* **31**

ENERDATA 2013 Global Energy and CO2 Data Online: http://services.enerdata.net/

Gollier C 2012 *Pricing the Planet's Future: The Economics of Discounting in an Uncertain World* (Princeton University Press) Online: http://books.google.de/books?hl=en&lr=&id=cFtCoc4VdHYC&oi=fnd&pg=PP2&dq=christian+gollier+2012&ots=J42q3nrnxR&sig=T3sPLN0lBr4xQqG3iAB6TOM_i4w

Gros D and Alcidi C 2010 The impact of the financial crisis on the real economy *Intereconomics* **45** 4–20

Hatfield-Dodds S 2013 Climate change: All in the timing *Nature* **493** 35–6

Hotelling H 1931 The economics of exhaustible resources *The Journal of Political Economy* **39** 137–75

IMF 2012 *World Economic Outlook 2012* (International Monetary Fund) Online: http://www.imf.org/external/pubs/ft/weo/2012/02/index.htm

Kriegler E, Weyant J P and et al. 2013 The Role of Technology for Achieving Climate Policy Objectives: Overview of the EMF27 Study on Global Technology Strategies and Climate Policy Scenarios *Clim. Change* **submitted**

Leimbach M, Bauer N, Baumstark L and Edenhofer O 2010a Mitigation Costs in a Globalized World: Climate Policy Analysis with REMIND-R *Environmental Modeling and Assessment* **15** 155–73

Leimbach M, Bauer N, Baumstark L, Luken M and Edenhofer O 2010b Technological Change and International Trade-Insights from REMIND-R *The Energy Journal* **31** 109–36

Lotze-Campen H, Müller C, Bondeau A, Rost S, Popp A and Lucht W 2008 Global food demand, productivity growth, and the scarcity of land and water resources: a spatially explicit mathematical programming approach *Agricultural Economics* Online: http://doi.wiley.com/10.1111/j.1574-0862.2008.00336.x

Luderer G, Bertram, C, Calvin K, De Cian E and Kriegler E 2013a Implications of weak near-term climate policies on long-term climate mitigation pathways *Clim. Change*

Luderer G, Bosetti V, Jakob M, Leimbach M, Steckel J, Waisman H and Edenhofer O 2012a The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison *Climatic Change* **114** 9–37

Luderer G, DeCian E, Hourcade J-C, Leimbach M, Waisman H and Edenhofer O 2012b On the regional distribution of mitigation costs in a global cap-and-trade regime *Climatic Change* **114** 59–78

Luderer G, Leimbach M, Bauer N, Kriegler E, Aboumahboub T, Curras T A, Baumstark L, Bertram C, Giannousakis A, Hilaire J, Klein D, Mouratiadou I, Pietzcker R, Piontek F, Roming N, Schultes A, Schwanitz V J and Strefler J 2013b *Description of the REMIND Model (Version 1.5)* (SSRN Working Paper 2312844) Online: http://papers.ssrn.com/abstract=2312844

Luderer G, Pietzcker R C, Kriegler E, Haller M and Bauer N 2012c Asia's role in mitigating climate change: A technology and sector specific analysis with ReMIND-R *Energy Economics* Online: http://www.sciencedirect.com/science/article/pii/S0140988312001661

Lueken M, O. Edenhofer, B. Knopf, M. Leimbach, G. Luderer and N. Bauer 2011 The role of technological availability for the distributive impacts of climate change mitigation policy *Energy Policy* **39** 6030–9

Manne A, Mendelsohn R and Richels R 1995 MERGE : A model for evaluating regional and global effects of GHG reduction policies *Energy Policy* **23** 17–34

Manne A S and Richels R G 2001 An alternative approach to establishing trade-offs among greenhouse gases *Nature* **410** 675–7

Masui T, Matsumoto K, Hijioka Y, Kinoshita T, Nozawa T, Ishiwatari S, Kato E, Shukla P R, Yamagata Y and Kainuma M 2011 An emission pathway for stabilization at 6 Wm−2 radiative forcing *Climatic Change* **109** 59–76

Matthews H D, Gillett N P, Stott P A and Zickfeld K 2009 The proportionality of global warming to cumulative carbon emissions *Nature* **459** 829–32

Meinshausen M, Meinshausen N, Hare W, Raper S C B, Frieler K, Knutti R, Frame D J and Allen M R 2009 Greenhouse-gas emission targets for limiting global warming to 2°C *Nature* **458** 1158–62

Meinshausen M, Raper S C B and Wigley T M L 2011a Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 1: Model description and calibration *Atmos. Chem. Phys.* **11** 1417–56

Meinshausen M, Smith S J, Calvin K, Daniel J S, Kainuma M L T, Lamarque J-F, Matsumoto K, Montzka S A, Raper S C B, Riahi K, Thomson A, Velders G J M and Vuuren D P P van 2011b The RCP greenhouse gas concentrations and their extensions from 1765 to 2300 *Climatic Change* **109** 213–41

Meinshausen M, Wigley T M L and Raper S C B 2011c Emulating atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 – Part 2: Applications *Atmos. Chem. Phys.* **11** 1457–71

Mendelsohn R, Sterner T, Persson U M and Weyant J P 2008 Comments on Simon Dietz and Nicholas Stern's Why Economic Analysis Supports Strong Action on Climate Change: A Response to the Stern Review's Critics *Review of Environmental Economics and Policy* **2** 309–13

Morgan T 2008 *Reforming energy subsidies: Opportunities to contribute to the climate change agenda* (UNEP)

Nordhaus W D 2007 A Review of the" Stern Review on the Economics of Climate Change" *Journal of Economic Literature* 686–702

Nordhaus W D and Yang Z 1996 A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies *The American Economic Review* **86** 741–65

Purdey J 2006 *Anti-Chinese Violence in Indonesia, 1996-1999* (University of Hawaii Press)

Ramsey F P 1928 A MAthematical Theory of Saving *The Economic Journal* **XXXVIII** 543–59

Rogelj J, Meinshausen M and Knutti R 2012 Global warming under old and new scenarios using IPCC climate sensitivity range estimates *Nature Climate Change* **2** 248–53

Schneider von Deimling T, Meinshausen M, Levermann A, Huber V, Frieler K, Lawrence D M and Brovkin V 2012 Estimating the near-surface permafrost-carbon feedback on global warming *Biogeosciences* **9** 649–65

Stern N 2007 The economics of climate change - The Stern review

Tavoni M, De Cian E, Luderer G, Steckel J and Waisman H 2012 The value of technology and of its evolution towards a low carbon economy *Climatic Change* **114** 39–57

UNEP 2012 The Emissions Gap Report Online: http://www.unep.org/publications/ebooks/emissionsgap2012

United Nations 2002 Report of the International Conference on Financing for Development Online: http://www.unmillenniumproject.org/documents/07_aconf198-11.pdf

Van Vuuren D, Edmonds J, Kainuma M, Riahi K and Weyant J 2011a A special issue on the RCPs *Climatic Change* **109** 1–4

Van Vuuren D, Stehfest E, den Elzen M, Kram T, van Vliet J, Deetman S, Isaac M, Klein Goldewijk K, Hof A, Mendoza Beltran A, Oostenrijk R and van Ruijven B 2011b RCP2.6: exploring the possibility to keep global mean temperature increase below 2°C *Climatic Change* **109** 95–116

Weitzman M L 2007 A review of the Stern Review on the economics of climate change *Journal of Economic Literature* **45** 703–24

Wigley T M L and Raper S C B 2001 Interpretation of High Projections for Global-Mean Warming *Science* **293** 451–4

Wilson C, Grubler A, Bauer N, Krey V and Riahi K 2013 Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Climatic Change* 1–15

Chapter 7

Synthesis and Outlook

This thesis set out to improve the understanding of the techno-economic achievability of stringent climate mitigation targets. We have analyzed the general structure of required energy system transformations, and focused on the role of variable renewable energies and the transport sector. The work documents the usefulness of large-scale energy-economy-climate models for exploring the full spectrum of mitigation scenarios with differing technology and policy options. Analysis and results strongly rely on the IAM REMIND, which over the course of this thesis was continually analyzed, tested, and further developed by the author of this thesis and several colleagues. To improve robustness of findings, two chapters present results from model comparison studies, bringing together a number of different IAMs.

Our results show that achieving stringent climate targets is possible at moderate economic costs, as long as comprehensive mitigation action is started without further delay, and relevant technologies can be up-scaled as currently expected. The decarbonization of the power sector hinges on the availability of solar power, and system integration challenges have a substantial impact on technology choices. The transport sector is a barrier to early decarbonization, but it does not seem insurmountable: very low transport emissions can be reached through a number of possible routes.

The following section summarizes the findings of Chapters 2–6. The three overarching themes are taken up in the "Synthesis and Discussion" section, which brings together findings from the individual chapters to extract robust insights and the most relevant policy conclusions. A discussion of the employed tool, namely IAMs, illustrates the continuous process of model development, validation, and improvement, using examples from this thesis. The thesis closes with promising areas for future research.

7.1 Summary of results

Chapter 2: Asia's role in mitigating climate change

This chapter develops an innovative and enhanced metric that attributes emission reductions between reference and climate mitigation scenarios to specific technologies. It thereby facilitates discerning technologies and sectors that contribute most to mitigation, pointing out enabling factors as well as possible bottlenecks of the required energy sys-

tem transformation. We apply this metric to REMIND mitigation scenarios performed in the course of the "Asian Modeling Exercise". We also take a specific look at Asia and its contributions to climate mitigation by adding a scenario in which Asia follows a counterfactual "no climate policy" scenario until 2020 and only starts mitigating in 2025.

A number of policy-relevant conclusions emerge from our analysis: First, we find that Asia plays a pivotal role in the global efforts to achieve climate stabilization. Asia currently accounts for almost two fifth of global emissions, and its share is projected to grow further, both in the reference and the climate policy scenarios. Clearly, without involvement of Asian countries, ambitious climate targets cannot be reached. Reconciling the legitimate priorities of Asian developing countries in terms of development and economic prosperity with the requirements of global climate change mitigation requires a substantial deviation from current emission trends and large-scale deployment of low-carbon technologies.

On the global scale, we find that the power sector has many decarbonization options, with non-biomass renewables contributing most to the decarbonization of the power sector. Emissions from non-electric energy demand are more difficult to reduce, with decarbonization strongly relying on bioenergy in combination with CCS as well as energy efficiency and demand reductions. Consequently, much larger emission reductions are realized in the power sector, and the bulk of residual emissions originate from the provision of transport fuels and heat energy supply. This result is in line with the findings of the RECIPE project (Luderer et al., 2011), and suggests that the development of advanced mitigation options for transport and other non-electric energy demand are of crucial importance for the cost and achievability of low stabilization targets.

Finally, our results emphasize the long-term benefits of early implementation of climate policy. We performed a stylized analysis that contrasts the scenario with immediate and globally coordinated climate policy to a scenario of delayed participation of Asian developing countries. Our results demonstrate that early adoption of climate policy does not only result in near-term emission reductions, but also avoids lock-in into carbon intensive infrastructure and thus leads to a much higher long-term mitigation potential, in particular in China and India.

Chapter 3: The role of renewable energy in climate stabilization

This chapter provides a comprehensive assessment of renewable energy deployment across a large number of energy-economy-emission models. We discuss how the deployment changes under climate policies, and the impact of technology availability on energy systems and mitigation costs. We find that the use of renewable energy sources (RES) increases substantially with the stringency of climate policy, such that RES become the dominant energy source under stringent stabilization targets: while the model median of the RES share in electricity production in 2050 (2100) is only $\sim$20% (30%) without climate policies, it increases to $\sim$40% (60%) in a 550 ppm CO_2e mitigation scenario and $\sim$50% (70%) in a 450 ppm CO_2e mitigation scenario. In models with high RES shares, the contribution from the VRE wind and solar is also particularly high.

The analysis also confirms a potential bottleneck for the decarbonization of the energy system found in Chapter 2: transport, buildings and industry strongly rely on solid, liq-

uid and gaseous energy carriers, with biomass as the (almost) exclusive decarbonization option. Accordingly, scenarios in which biomass availability is restricted to 100 Exajoule (EJ) show markedly increased mitigation costs (mitigation costs for the 450 ppm CO_2e scenario increase by 50–75%). Mitigation costs rise even further if additionally wind and solar use is limited to 20% of electricity generation (mitigation costs increase by 55–110%). While this bottleneck certainly is relevant, it also comes with a reservation and requires further research: the reliance on bioenergy may be somewhat overestimated due to the fact that for historical reasons, many IAMs have focused on the electricity sector and only include limited representation of heat and mobility provision from non-biomass RES, such as solar heat or hydrogen electrolysis to power fuel cell vehicles.

The general findings are robust across most models, but the exact values of RES deployment differ widely. As a first step towards a better understanding of why the results differ so much, we discuss three main determinants of VRE deployment[1]: technology costs, resource potentials, and system integration mechanisms. We find a wide range of differing input assumptions, which partly seem to lie outside of plausible ranges. Especially resource potentials and system integration mechanisms require further research to be updated and improved.

Chapter 4: Using the sun to decarbonize the power sector

This chapter deepens the analysis of variable renewable energies: It uses the energy-economy-climate model REMIND to investigate the economic importance of the solar technologies photovoltaics and concentrating solar power for the decarbonization of the electricity sector. To do so, we created three intermediate outputs, which can also be used to augment the representation of solar power technologies in other large-scale energy-economy-models: estimates of current and future investment cost, a consistent resource potential data set for the two solar technologies, and a simplified representation of system integration costs.

The calculated scenarios project a dominant role for solar technologies in the decarbonization of the power sector. Solar electricity will be the main source of electricity in the second half of the century, supplying 47% of the cumulated global electricity produced from 2010–2100 in a scenario with cost-efficient mitigation policies to achieve the 2°C target. Even without climate policy, solar becomes the main source of electricity after 2070. The analysis of system integration costs revealed that they are highly relevant for the competition between PV and CSP: Although PV consistently has lower direct levelized costs of electricity than CSP and is initially deployed faster, CSP catches up and overtakes PV at the end of the century due to lower integration costs of CSP.

In a climate policy world, the electricity system is dependent on having at least one solar technology available: excluding both PV and CSP leads to substantial increases in electricity prices, so that the average price from 2050 to 2100 is 280% higher than in 2010. Both technologies can partially substitute each other: In cost-optimal scenarios, PV and CSP complement each other, but if one of the two technologies faces deployment barriers,

[1] Bioenergy was not further analyzed in this publication, as three other articles of the model comparison project focused on bioenergy use (Klein et al., 2014; Rose et al., 2014; Popp et al., 2014).

the other can strongly increase its share in total electricity production and partially make up for the loss of the other technology.

The dominance of solar technologies for the power is quite robust to changing cost assumptions: Even under the most pessimistic view that the projected cost reductions are not realized and investment costs remain at current levels, solar technologies produce 20% of cumulated 2010–2100 electricity in a climate mitigation scenario.

Solar technologies could thus be characterized as a backstop technology for the power sector in most regions: they require a certain electricity price before being deployed, but then manage to decouple the electricity price from resource and carbon price increases, as they can supply large quantities of electricity in most world regions without escalating costs.

Chapter 5: Long-Term Transport Energy Demand and Climate Policy

The chapter builds on a model comparison study to analyze decarbonization pathways for the transport sector, and to test the hypothesis that the transport sector is more difficult to decarbonize than the non-transport sectors. To understand how model structure influences the results, we systematically analyze the various mitigation options along the chain of causality, including demand reduction, vehicle choice, energy conversion pathways and carbon capture and sequestration.

The different models project different decarbonization pathways, which strongly depend on the choice of technologies implemented and on the structure of the model. One could thus interpret the participating models as studies of different possible futures in which certain options (battery electric vehicles, fuel cell vehicles, large-scale sustainable biomass use in combination with CCS) become viable or not.

Some robust findings emerge: We find across all models a substantial delay of the transport sector decarbonization in the first half of the 21st century: relative emission reductions are reached 10–30 years later than in the non-transport sectors. Even in the most stringent policy scenario, transport strongly relies on liquid fuels until 2050: even in the strongest climate policy, more than 85% of transport final energy is in liquid form in all models except for WITCH-T. One can thus conclude that amongst the models studied, the hypothesis that the transport sector is more difficult to decarbonize than the non-transport sectors with a carbon price of plausible size is confirmed when looking at the time period before 2060.

In the long run, however, the three global models running until 2100 achieve deep emission reductions by 90% and more in the strong climate policy scenario. This almost complete decarbonization hinges on the use of advanced vehicle technologies in combination with carbon-free primary energy sources; here, especially biomass combined with CCS plays a crucial role. The extent to which earlier mitigation is possible strongly depends on the choice of technologies implemented and the structure of the model, with both partial-equilibrium models focusing on China proving to be less flexible.

Chapter 6: Economic mitigation challenges

In this chapter, we use a large number of scenarios calculated with the energy-economy-climate model REMIND to address the fundamental question of this thesis, namely the economic achievability of stringent climate targets. Our work maps out the trade-offs between the stringency of climate targets and economic mitigation challenges at a very high level of detail. It shows how a continuation of ineffective climate policies reduces the option space for future climate policy, increasing mitigation challenges and the reliance on technologies for removing CO_2 from the atmosphere.

Under optimistic assumptions about the outcome of current climate negotiations and technology availability, we estimate that achieving a likelihood of 67% of limiting global warming to 2°C would result in aggregated mitigation costs of 1.4% of Gross World Product. However, delaying comprehensive emission reductions by another 15 years pushes this target out of reach. In case of technology limitations, the urgency of reaching a global climate agreement is even higher. The temperature-cost tradeoff curves are highly convex, so costs increase disproportionally with increasing target stringency. We estimate that economic mitigation challenges become prohibitively high for temperature stabilization targets below ∼1.7°C.

A continuation of weak climate policies inevitably increases the risk of exceeding the 2°C threshold. Returning to 2°C in such a scenario will be difficult, and requires large-scale deployment of bioenergy in combination with CCS. We find that temperature levels in 2100 depend to a much higher extent on the availability of technologies than maximum 2010–2100 temperatures do: Unavailability of CCS shifts achievable target levels in 2100 up by almost 0.5°C. Our research also demonstrates that the effects on short-term consumption growth and energy prices as well as the redistribution of wealth induced by CO_2 pricing are crucial challenges of mitigation pathways consistent with the 2°C target. This finding points to potentially strong distributional effects of climate policies, which increase substantially if comprehensive climate policies are delayed further.

The results have important implications for climate policy. They show clear trade-offs between long-term climate targets and economic mitigation challenges. They also demonstrate that these trade-offs depend strongly on the start date of substantial emission reductions and technology availability. The longer the international community delays the implementation of comprehensive climate policies, the more critical these trade-offs will be.

7.2 Discussion of results and policy implications

7.2.1 Economic implications of low stabilization scenarios

The main result of this thesis has a positive note: Transforming the global energy system and economy to keep a reasonable likelihood (67%) of limiting global warming to below 2°C is achievable at moderate economic implications, such as aggregated and discounted consumption reductions by 1.4% of Gross World Product, or maximum decadal energy price increases below 25%. However, this result hinges on assumptions that some people would term “optimistic”, namely a near-term implementation of stringent global climate

policies and full availability of several technologies that are still in the demonstration phase.

Given the soberingly slow progress of UNFCCC climate negotiations in the last decades, it is important to analyze how the economic implications change under sub-optimal timing. Delaying stringent policies and extending the current period of fragmented and weak action will substantially increase mitigation costs, such that stringent climate targets might be pushed out of reach. Should the current weak climate policies be extended until 2030, the short-term transitional mitigation costs for keeping the 2°C target would increase three-fold compared to a world in which global cooperative action is decided on in 2015 and first deep emission reductions are achieved in 2020.

Technology availability is another relevant driver for mitigation costs. As the analysis in Chapters 3 and 6 reveals, changing the assumptions about technologies and their availability can increase mitigation costs substantially, thereby pointing out possible bottlenecks for a decarbonization of the energy system. Although none of the implemented technologies are totally new and untested, some (such as fuel cell vehicles, second-generation biofuel or large-scale carbon capture and sequestration) have not yet surpassed the demonstration phase and might therefore not live up to current expectations. For other technologies, additional barriers might appear or prove more problematic than expected. A prime example is biomass use, where sustainability and equity issues raise major questions about the large-scale application in future energy systems (Sagar and Kartha, 2007; Kahrl and Roland-Holst, 2010; Dornburg et al., 2010), and issues about the time scales of plant growth and land-use change raise questions about the actual contributions of biomass to emission reductions (Fargione et al., 2008; Searchinger et al., 2009; Melillo et al., 2009). This is especially relevant as total mitigation costs are most strongly influenced by the availability of biomass in combination with CCS. In contrast, Chapter 4 showed that the power sector decarbonization strongly hinges on the availability of solar power. Therefore, a larger (or smaller) shift in energy carrier use towards electricity than currently implemented in the model parameters would also increase (decrease) the relative importance of solar technologies compared to BECCS for climate change mitigation.

Our analysis also shows the importance of using a variety of metrics to better understand energy system transformations and to capture more aspects of economic implications of mitigation targets. Aggregated consumption losses are very relevant, but omit the distributional effects that climate policies can have – for such effects, energy prices can be a better suited metric, as low-income households spend a much higher share of their income on energy expenditures. Similarly, the total value of carbon emissions is a metric that can help to understand the scope of newly-created economic scarcities and the resulting challenges for international climate negotiations. While international transfers can ease the burden of mitigation efforts, the substantial size of the carbon market poses the risk that the resulting transfers become a “resource curse” for less-developed countries (Jakob et al., 2012).

7.2.2 Variable renewable energies

Chapters 2, 3 and 4 document the paramount importance of renewable energies and especially variable renewable energies[2] for the decarbonization of the power sector. Half of the models studied in Chapter 3 show renewable shares above 50% in 2050 and above 70% in 2100 in a stringent climate scenario with 450 ppm CO_2e in 2100. At the same time, Chapter 3 also documents substantial differences between the results of the different models. The detailed analysis of the three main determinants of VRE deployment, namely resource potential, technology costs and system integration mechanisms, revealed parameter ranges that can partially be explained with true uncertainty, but that are partially overestimated and leave room for model improvement (see Section 7.3.1).

Future decarbonized power sectors will include a substantial amount of solar and wind, which pose specific integration challenges due to their spatial and temporal heterogeneity. Representing these integration challenges in IAMs is necessary to calculate reasonable scenarios that neither under- nor overestimate the difficulty of decarbonizing the energy system. We find a wide variety of integration mechanisms in different IAMs, with some seeming overly strict, while others implement no or only very small integration costs.

Solar power becomes the dominant source of electricity in stringent mitigation scenarios. This is the result of a detailed investigation of how integration costs influence the deployment of solar power technologies, for which we augmented the representation of integration costs in REMIND and updated the parameters with current bottom-up estimates. Although the marginal integration costs (as implemented in REMIND) become larger than the direct technology costs for PV and wind, solar power supplies more than 45% of total 2010–2100 electricity in stringent mitigation scenarios.

This dominance is due to three factors: i) PV has shown substantial technology learning with resulting cost decreases in the past, which are expected to continue for the next years, ii) CSP has comparatively low integration costs as thermal storage overcomes day-night cycles and co-firing of hydrogen can overcome seasonal fluctuations, iii) all other technologies face either strongly rising emission costs (fossil technologies), limited resource and waste disposal potential (nuclear), strong demand from other sectors leading to competition for scarce resources (biomass, CCS) or a combination of high integration costs and a more limited potential than solar (wind).

Also, the structure of the model influences this result: REMIND is intertemporally optimizing, meaning it will invest into technologies even if they are initially more expensive than competing technologies, as long as they result in larger (discounted) long-term cost reductions. The scenarios can therefore be seen as optimal benchmarks of how a cost-efficient energy system transformation could look like. To realize these scenarios, policymakers need to design policy instruments that internalize the long-term benefits (such as knowledge spillovers) and support the relevant technologies, even if they initially are not competitive.

[2] In Chapter 2, VRE are subsumed under "non-biomass renewables". The missing part is mostly hydropower, which – due to limited deployment potentials – does not change strongly between reference and climate policy runs, therefore the results of the mitigation share analysis can be transferred to VRE.

7.2.3 Transport decarbonization

The relevance of the transport sector for climate change mitigation is analyzed in Chapters 2 and 5. Our research confirms the hypothesis that the transport sector is not very reactive to intermediate carbon prices (below 100–200 $\$/tCO_2$). Until 2050, transport decarbonization lags 10–30 years behind decarbonization of other sectors, and liquid fuels dominate the transport sector, supplying more than 85% of final energy demand.

In the long term, however, transportation does not seem to make stringent climate targets unachievable: As the price signals on CO_2 increase, transport emissions can be reduced substantially – if at least one of the following decarbonization routes can be scaled up massively:

- The use of low-carbon electricity for transportation, which is straightforward for trains, brings high but manageable costs for light duty vehicles, and is expected to pose a major challenge for freight.
- The use of low-carbon hydrogen, which is currently expected to come with larger capital cost markups, but requires less change of user behavior than battery-electric vehicles.
- The use of second-generation bioliquids from lignocellulosic feedstock, possibly combined with CCS to produce negative emissions.

All of these options are mostly technological and require only limited change of user behavior, but come at substantial capital costs and potentially lead to negative sustainability effects (biomass use). Furthermore, they come with limited potential vis-à-vis other transport objectives: bioliquids would not help to reduce air pollution or noise disturbance, and none of the technologies would address congestion or land requirement. Transport emissions can also be reduced through other options for changing transportation decisions, such as modal shift to mass transit, shift to smaller and more efficient vehicles, or reduction of travel demand, but these behavior- and infrastructure-related options are rarely represented in IAMs with their techno-economic focus. First forays into this area were performed in the last years (Anable et al., 2012; Girod et al., 2013), but more attention is required in the future.

7.2.4 Policy Conclusions

A number of policy conclusions can be drawn from the research performed for this thesis.

1. To achieve the stringent climate mitigation targets publicly voiced by most policymakers, it is paramount to act fast. Delaying comprehensive mitigation action raises the total cost of achieving a certain target, strongly increases the short-term transitional burden, and aggravates the reliance on critical technologies that are either not yet fully developed or that might endanger other sustainability objectives.
2. The most important long-term policy measure for climate change mitigation is to install a price on carbon, either as a carbon tax or a market for emission permits. A

price on carbon leads all market actors pursuing carbon-emitting activities across all economic sectors to realize the scarcity of the atmosphere and to internalize it into their decisions (Knopf et al., 2010).

3. The power sector can be seen as a low-hanging fruit with many options for decarbonization – a low-hanging fruit that should be harvested soon: The substantial growth of electricity demand in many developing economies poses the risk of substantial lock-ins into carbon-heavy infrastructure. Should an economy-wide carbon price be difficult to implement for politico-economical or institutional reasons, a short-term dedicated regulation of the electricity system to phase out construction of new coal power plants and thereby prevent such a carbon lock-in seems advisable: The total new capacity of coal power plants without CCS that is globally installed between 2015 and 2025 is reduced from 900 Gigawatt (GW) in a reference scenario to below 40 GW in a cost-efficient scenario that limits warming below 2°C. Dedicated support for renewables as well as flexibility options for the power system could flank such a policy and additionally address another sustainability objective, namely energy access.

4. Photovoltaics, concentrating solar power and wind power are the most promising technologies for the decarbonization of the power sector due to their large resource base, minor risks, and limited public opposition. However, temporal variability poses a challenge to the integration of large shares of wind and solar power. It therefore seems advisable to push for a "reality check" by implementing policies to quickly expand VRE energies until they reach combined generation shares around 25–40% (Lehmann et al., 2012). According to current estimates, at such shares variability starts to become a challenge without yet substantially endangering system stability. This gives market actors and policymakers time and motivation to develop technical and institutional approaches to increases the flexibility of the power sector, both on the demand and on the supply side. Should the challenge of temporal variability prove to be very costly, rendering climate scenarios with high shares of VRE unrealistic, there would remain time to research and develop other options for power sector decarbonization.

5. There is no simple answer to decarbonizing the transport sector. Advanced vehicle technologies allow the use of low-carbon energy carriers and can therefore achieve very high emission reductions, but entail substantial capital costs and are only usable for a subset of transport modes. Increasing vehicle efficiency can help reduce emissions in all transport modes, but "split incentive" problems as well as observed high private discount rates when evaluating energy-efficiency investments lead to less-than-efficient market outcomes. The substantial influence of non-monetary drivers on transport choices makes it necessary and promising to investigate various policy instruments beyond pricing carbon that can lead to less carbon-intensive travel, including such diverse measures as land-use and infrastructure planning targeted towards mass transit and non-motorized modes, efficiency standards, or awareness campaigns and travel plans.

6. CCS, especially when applied to the second-generation production of liquids from ligno-cellulosic biomass, should be further researched and tested in demonstration projects. While CCS does not seem essential for the power sector, it seems to offer

unique possibilities to reduce emissions in the transport sector, in the provision of heat, as well as in some industrial processes. However, it currently is still a speculative option, which additionally faces public opposition in many regions. Hence, substantial research and testing of CCS technologies and processes is required.

7.3 Discussion of methods

7.3.1 Improving IAMs

IAMs can be useful tools for policy advice and policy assessment: their scenarios allow analyzing and discussing the effects of policy instruments. However, the future is inherently uncertain and unknowable. IAM scenarios can only hope to present plausible pathways that are internally consistent. The question of how to validate IAMs through systematic approaches has been around for decades without providing definitive answers such as the development of widely-accepted routines, but it has gained new attention in the last years (Risbey et al., 1996; Schneider, 1997; Parker et al., 2002; Risbey et al., 2005; Van Vuuren et al., 2010; DeCarolis et al., 2012; Schwanitz, 2013).

An essential element of quality control of IAMs is documentation and transparency: IAMs are built on such enormous amounts of data and equations that it is impossible to comprehend and critically assess the embodied assumptions unless they are extensively and transparently documented and made publicly available (Risbey et al., 1996; Schneider, 1997; Craig et al., 2002; van der Sluijs, 2002; DeCarolis et al., 2012; Schwanitz, 2013; Luderer et al., 2013). Additionally, IAMs contain a substantial number of value judgments, which need to be communicated clearly and explicitly (Stanton, 2011). Only then can policymakers be enabled to critically assess IAM results and make informed use of them (Risbey et al., 1996; Schneider, 1997; Craig et al., 2002). Funding agencies like the EU commission have started to address these issues by requiring transparent and publicly available documentation when funding modeling projects. Also, model comparison exercises can contribute to developing documentation standards, providing input data bases, and defining standard diagnostic variables and testing procedures for IAMs (Schwanitz, 2013).

As discussed in the introduction, each IAM is fundamentally formed by its modelers and necessarily represents the modeler's perception of the world. When developing an IAM, each choice about which value to use for an uncertain parameter, which functional form to choose, which interaction to represent or which input data to use, influences the results (Risbey et al., 1996; Schneider, 1997; van der Sluijs, 2002; Schwanitz, 2013). As IAMs deal with the future, they cannot be exhaustively validated against the real world in advance (Craig et al., 2002; Weyant, 2009; DeCarolis et al., 2012). Therefore, model comparison exercises such as those presented in Chapters 3 and 5 are indispensable, as they force modelers to critically reflect their choices and to explain the logic behind their model's results. Furthermore, they capture some of the real-world uncertainty that often has to be omitted for reasons of numerical complexity when programming large-scale energy-economic models (Craig et al., 2002).

The model comparison exercises presented in this thesis demonstrate that results from different IAMs can diverge quite dramatically. It is important to analyze the drivers for the divergence. Once these drivers are identified, it is possible to evaluate them by comparing them to more detailed models and stylized facts (Blanford et al., 2012; Chaturvedi et al., 2012; Clarke et al., 2012; Schwanitz, 2013). Ideally, this allows modelers to determine whether the reasons for the divergence are valid, such as structural uncertainty, whether the drivers are more complex and need to be modeled with greater detail to yield plausible results, or whether the observed phenomenon is actually a model artifact that should be removed in the next version of that model.

Chapters 3 and 5 are valuable steps in this direction: Chapter 3 discusses the drivers of VRE deployment, thereby allowing the reader to evaluate where models represent real uncertainty, and where the results are driven by outdated input parameters or unrealistic limitations. While many parameterizations lie within a plausible range, areas for improvement are identified: some models include unrealistic restrictions on VRE integration in the form of hard upper bounds that limit VRE shares to levels already seen in some real-world energy systems. Also, widely varying VRE potentials are documented – although some variation is realistically to be expected due to different plausible choices on technology parameters and land exclusion criteria, the huge differences observed highlight the need for improved VRE resource potentials. We address these needs in Chapter 4, where we present a new consistent solar resource potential dataset as well as a flexible representation of VRE integration constraints. Chapter 5 documents different representations of the transport sector in several IAMs. Again, it is possible to identify the three types of divergence: the differing reliance on either battery-electric vehicles or hydrogen vehicles in CHN-T, GCAM, PECE and REMIND reflects the real uncertainty about future technology cost developments of these relatively novel technologies. Other limitations seem rather like "model artifacts", e.g., the price-inflexible mobility demand in CHN-T, PECE and WITCH-T, the omission of hydrogen vehicles in WITCH-T, or the omission of endogenous efficiency-improvements in GCAM and REMIND. Some areas like modal shift are not well represented in most models and require further detailed analysis and modeling work.

As one of the main goals of integrated assessment modeling is to provide policy-relevant insights, explicit and dedicated stakeholder engagement can improve IAM-based policy assessments. Although stakeholder engagement can be quite complex and demanding, and no universal approach exists, it can entail a number of benefits, such as increasing the relevance of model results, building trust and advancing stakeholder comprehension of the strengths and limitations of models, increasing legitimation for the value judgments incorporated in the model, or boosting visibility (Craig et al., 2002; Kloprogge and Sluijs, 2006; Voinov and Bousquet, 2010; Krueger et al., 2012; Schmid, 2013).

7.3.2 Neoclassical economic theory

On a very fundamental level, the results presented in this thesis are based on aspects and by-products of neoclassical economic growth theory or its commonly accepted simplifications. These include assuming rational utility-maximizing agents, measuring welfare through the logarithm of consumption, or using the Negishi approach to ensure intertemporal budget closure, thereby implying no permanent transfers between richer and less

rich regions (Stanton, 2011). These assumptions are part of a theory that successfully describes some aspects of the society we live in (Jones and Romer, 2010), but fails to describe other aspects. For brevity's sake, the discussion will be limited to the basic building block of neoclassical economics: the individual actor. Real people are not the purely rational self-utility-maximizing agents with fixed preferences that are the basis of most large-scale economic models (Henrich et al., 2001; Hodgson, 2003; Henrich et al., 2005; DellaVigna, 2009), but are rather affected by bounded rationality (Simon, 1982; Gigerenzer and Selten, 2002; Kahneman, 2003a). They can show altruism and reciprocity (Rabin, 1993; Levine, 1998; Bolton and Ockenfels, 2000; Fehr and Gächter, 2002), show aversion to inequity and favor fairness (Kahneman et al., 1986a,b; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000), have the capacity to cheat and betray each other, develop institutions to overcome personal shortcomings (Ostrom, 1990), be swayed by status considerations, peers and advertising to desire products that do not increase their welfare (Hoch and Ha, 1986; Hoch and Loewenstein, 1991; Hodgson, 2003; Bowles and Park, 2005; Thaler and Sunstein, 2008; Rozendaal et al., 2009), change their lifestyle to strive for a better world, or suffer from time-inconsistencies and self-control problems (Laibson, 1997; Muraven and Baumeister, 2000; Gul and Pesendorfer, 2001; Fehr and Rockenbach, 2003; Hepburn et al., 2010).

It can be argued that some of these aspects are actually represented in the Ramsey growth framework, especially altruism: The assumption of a constant discount rate over all time could be interpreted as a perfectly altruistic approach, as the welfare of future generations is accounted for as if it were one's own (Phelps and Pollak, 1968; Stephan et al., 1997; Dasgupta, 2008). However, others challenge this view, stating that there are neither sufficient empirical nor sufficient ethical grounds to justify discounting the welfare of two different future generations against each other along the same lines one discounts two events within the current generation's lifetime (Schelling, 1995; Rabl, 1996; Sumaila and Walters, 2005; Roemer, 2011). Also, there is no intra-generational altruism embedded in the Negishi approach used to solve multi-region Ramsey models, whereas altruism in the real world clearly not only extends to next generations, but also across one generation (Stanton, 2011).

Over the last decades, a variety of economic research domains have questioned concepts and assumptions of neoclassical economics and developed new notions and paradigms, examples being the importance of human behavior beyond the "homo oeconomicus" (Fehr and Schmidt, 1999; Akerlof and Kranton, 2000; Fehr and Gächter, 2000; Fehr and Fischbacher, 2002; Kahneman, 2003b; Gintis et al., 2003; Fehr and Rockenbach, 2003; Thaler and Benartzi, 2004; Cox, 2004; Henrich et al., 2005; Gneezy and List, 2006; Fudenberg, 2006; Camerer et al., 2011), the factors influencing well-being and welfare besides direct consumption (Diener et al., 1999; Diener, 2000; Frey and Stutzer, 2002; Tella et al., 2003; Kahneman et al., 2003; Layard, 2006; Easterlin, 2006; Kahneman, 2011) including the capability approach (Sen, 1985a,b; Sen and Nussbaum, 1993; Atkinson, 1999; Robeyns, 2005), or the role of institutions for the governance of commons (Ostrom, 1990; Hodgson, 1998; Ostrom et al., 1999; Dietz et al., 2003; Ostrom et al., 2007; Ostrom, 2009).

Another relevant issue for the economic analysis of policies to overcome market failures and internalize externalities like climate change is the interplay between intrinsic motivation and external incentives. Research has shown that depending on the behavior at

hand and the framing of the incentive, external incentives can either crowd out or crowd in intrinsic motivation, thereby reducing or increasing the effect of policy interventions (Frey and Jegen, 2001; Bowles and Hwang, 2008; Bowles and Polanía-Reyes, 2012).

These aspects allow for very different developments of the real world than those seen in the modeled scenarios mostly based on neoclassical economic theory; developments that might be more positive or negative. Although a detailed quantitative analysis based in economic theory is a valuable and necessary component of policy assessment, long-term projections should be complemented with other approaches, one example of which are more narrative scenarios that explore different development possibilities for human societies and nations. Ultimately, economic quantities don't develop according to natural laws, but fundamentally depend on the underlying societies, the values and norms they uphold and the institutions they develop (Risbey et al., 1996; Raskin, 2008; Raskin et al., 2010; Rosen et al., 2010).

7.4 Suggestions for future research

Climate change mitigation is one of the fundamental challenges of this century. Assessment of mitigation policies will be continually required, and IAMs are useful tools for long-term decarbonization scenarios. Policies change, economies evolve faster or stagnate, technologies are further improved or meet unforeseen barriers – all of these effects will lead to different future scenarios, and require updating and improving of IAMs. Also, IAMs are very aggregated models with a large number of stylized representations of sub-scale processes. In the process of testing and improvement, it turns out that some of these representations influence the results more than others. These representations then warrant a more in-depth analysis, possibly with detailed bottom-up models.

In the course of this thesis, several relevant aspects of mitigation pathways were discussed, and a number of open points have been identified, which refer to both IAMs in general as well as REMIND. These points include distribution and equity, demand side heterogeneity, stationary energy use, VRE integration, and additional transport policies.

First and foremost is the topos of distribution and equity: which economic costs and benefits accrue in which countries or regions, and which parts of the population are most affected? What are the real-world trade-offs between efficiency and equity? Where does the additional burden of mitigating climate change threaten the fulfillment of basic human needs and sustainable development, and where can it be borne without noticeable impacts to welfare and living conditions? What additional policy instruments can be used to soften the impact of mitigation policies on the poorest? What rents can be tapped to provide the funds necessary for transforming the global energy system? To address these questions, IAMs require disaggregation and down-scaling, as currently millions of heterogeneous people are aggregated into a single average for each region.

Differentiating individual income groups would also allow modelers to improve model realism: real-world energy demands as well as reactions to policies and price changes are strongly influenced by factors like personal wealth or urbanization (van Ruijven et al., 2011; Krey et al., 2012), which cannot be reproduced in models using average values

alone. Thus, differentiating heterogeneous consumers would be a first step towards more policy relevance on distributional questions as well as higher realism of model dynamics.

On a more techno-economic level, many smaller research questions remain. To better understand the energy transformation necessary for stringent climate protection, an important next step would be to investigate the decarbonization processes for the third type of energy services, namely heating and process energy (termed "stationary non-electric" in REMIND). These energy services currently rely strongly on solid, liquid and gaseous fuels, and therefore – like the transport sector – prove to be more difficult to decarbonize than the power sector. However, different types of heating and process energy services are substantially different in their decarbonization. Heat pumps might offer comparatively efficient routes to use electricity for heating in low population density settlements, while in other regions solar thermal might be a viable route. In general, energy demand for heating can be substantially reduced through thermal insulation, thus the aggregated capital-energy trade-off in the building sector is an important aspect requiring further investigation. For industry processes, the currently used energy carriers often not only supply heat but also chemical or structural properties, therefore substitution with other energy carriers cannot easily be analyzed at an aggregated level but needs to be understood at a process-based level.

Although the current work has improved the representation of the system integration challenge of variable renewable energies, substantial work remains to be done for REMIND and most other IAMs. A region-specific analysis of the system flexibility required at different mixes of solar and wind power would allow modelers to derive more robust integration costs that are more useful to national policymakers. Also, the interactions between the different energy sectors are a very relevant aspect for further investigation. Currently discussed flexibility measures include demand response (Cappers et al., 2012), "power to heat" in combination with district heating systems (heat is cheaper to store than electricity) (Arteconi et al., 2012; Hedegaard et al., 2012a), power to hydrogen or gas (Steward et al., 2009), transport electrification or hydrogen use (Andrews and Shabani, 2012; Fernandes et al., 2012; Hedegaard et al., 2012b), all of which connect the different parts of the energy system and thus require an improved understanding of the temporal patterns in the sub-parts (Mathiesen et al., 2012). A necessary step for the analysis of viable decarbonization strategies with high VRE shares is the development of intermediate-scale models that have a higher temporal detail than IAMs, but still manage to represent the interactions between the different energy use types (Lund et al., 2010; Kiviluoma and Meibom, 2010).

When analyzing and modeling the decarbonization of the transport sector, it is important to think about all relevant drivers that determine travel demand and travel choices, not only vehicle and fuel costs. People are influenced in their mobility choices by a number of additional factors, ranging from technical aspects like travel speed, recharging infrastructure, or land use, to "softer" aspects like comfort, lifestyles, social norms, or status consumption. In parallel to the variety of influencing factors, there are also a large number of possible transport policies besides "pricing carbon" that could enable the transformation of the transport sector towards lower CO_2 emissions (Banister et al., 2011). First approaches to include lifestyles and socio-cultural factors into techno-economic models of transport are being developed (Anable et al., 2012; Schafer, 2012), but further work is required to operationalize them for IAMs. One option currently employed is to fol-

low a scenario approach, where one scenario with exogenous standard travel demand is compared to another scenario with model-exogenous lower travel demand, motivated by some assumed additional policy that influences behavior. To make these analyses more meaningful, it would be useful to explicitly include these policies in the model and make the choice model-endogenous (Schafer, 2012). This poses a substantial challenge, as it requires attributing economic, political and social costs to transport policies such as vehicle efficiency standards, speed limits, or transit-oriented development. In addition, more bottom-up research is necessary to derive better estimates for the aggregated effects of various non-price policies.

Also, policies geared towards reduction of CO_2 emissions from the transport sector can have substantial co-benefits. In fact, benefits in other areas can be the much larger: transport policies targeted at other pressing issues like air pollution or congestion can at the same time induce changes that are beneficial for mitigating climate change (Creutzig and He, 2009). Investigating these interactions to better understand the marginal costs of climate policies as well as the politico-economical synergies of implementing policies that address several issues at once will lead to improved policy assessment.

References

Akerlof, G. A., Kranton, R. E., 2000. Economics and identity. The Quarterly Journal of Economics 115 (3), 715–753.
http://qje.oxfordjournals.org/content/115/3/715

Anable, J., Brand, C., Tran, M., Eyre, N., Feb. 2012. Modelling transport energy demand: A socio-technical approach. Energy Policy 41 (0), 125–138.
http://www.sciencedirect.com/science/article/pii/S030142151000635X

Andrews, J., Shabani, B., Jan. 2012. Re-envisioning the role of hydrogen in a sustainable energy economy. International Journal of Hydrogen Energy 37 (2), 1184–1203.
http://www.sciencedirect.com/science/article/pii/S0360319911022841

Arteconi, A., Hewitt, N., Polonara, F., May 2012. State of the art of thermal storage for demand-side management. Applied Energy 93, 371–389.
http://www.sciencedirect.com/science/article/pii/S0306261911008415

Atkinson, A. B., 1999. The contributions of amartya sen to welfare economics. Scandinavian Journal of Economics 101 (2), 173–190.
http://onlinelibrary.wiley.com/doi/10.1111/1467-9442.00151/abstract

Banister, D., Anderton, K., Bonilla, D., Givoni, M., Schwanen, T., 2011. Transportation and the environment. Annual Review of Environment and Resources 36 (1), 247–270.
http://www.annualreviews.org/doi/abs/10.1146/annurev-environ-032310-112100

Blanford, G. J., Rose, S. K., Tavoni, M., Dec. 2012. Baseline projections of energy and emissions in asia. Energy Economics 34, Supplement 3, S284–S292.
http://www.sciencedirect.com/science/article/pii/S0140988312001764

Bolton, G. E., Ockenfels, A., 2000. ERC: a theory of equity, reciprocity, and competition. American Economic Review 90 (1), 166–193.
http://www.aeaweb.org/articles.php?doi=10.1257/aer.90.1.166

Bowles, S., Hwang, S.-H., Aug. 2008. Social preferences and public economics: Mechanism design when social preferences depend on incentives. Journal of Public Economics 92 (8–9), 1811–1820.
http://www.sciencedirect.com/science/article/pii/S0047272708000431

Bowles, S., Park, Y., 2005. Emulation, inequality, and work hours: Was thorsten veblen right?*. The Economic Journal 115 (507), F397–F412.
http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0297.2005.01042.x/abstract

Bowles, S., Polanía-Reyes, S., Jun. 2012. Economic incentives and social preferences: Substitutes or complements? Journal of Economic Literature 50 (2), 368–425.

Camerer, C. F., Loewenstein, G., Rabin, M., 2011. Advances in Behavioral Economics. Princeton University Press.

Cappers, P., Mills, A., Goldman, C., Wiser, R., Eto, J. H., Sep. 2012. An assessment of the role mass market demand response could play in contributing to the management of variable generation integration issues. Energy Policy 48, 420–429.
http://www.sciencedirect.com/science/article/pii/S0301421512004521

Chaturvedi, V., Waldhoff, S., Clarke, L., Fujimori, S., Dec. 2012. What are the starting points? evaluating base-year assumptions in the asian modeling exercise. Energy Economics 34, Supplement 3, S261–S271.
http://www.sciencedirect.com/science/article/pii/S0140988312001090

Clarke, L., Krey, V., Weyant, J., Chaturvedi, V., Dec. 2012. Regional energy system variation in global models: Results from the asian modeling exercise scenarios. Energy Economics 34, Supplement 3, S293–S305.
http://www.sciencedirect.com/science/article/pii/S0140988312001624

Cox, J. C., 2004. How to identify trust and reciprocity. Games and Economic Behavior 46 (2), 260–281.
http://www.sciencedirect.com/science/article/pii/S0899825603001192

Craig, P. P., Gadgil, A., Koomey, J. G., 2002. WHAT CAN HISTORY TEACH US? a retrospective examination of long-term energy forecasts for the united states*. Annual Review of Energy and the Environment 27 (1), 83–118.
http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.27.122001.083425

Creutzig, F., He, D., Mar. 2009. Climate change mitigation and co-benefits of feasible transport demand policies in beijing. Transportation Research Part D: Transport and Environment 14 (2), 120–131.
http://www.sciencedirect.com/science/article/pii/S1361920908001478

Dasgupta, P., Dec. 2008. Discounting climate change. Journal of Risk and Uncertainty 37 (2-3), 141–169.
http://link.springer.com/article/10.1007/s11166-008-9049-6

DeCarolis, J. F., Hunter, K., Sreepathi, S., Nov. 2012. The case for repeatable analysis with energy economy optimization models. Energy Economics 34 (6), 1845–1853.
http://www.sciencedirect.com/science/article/pii/S0140988312001405

DellaVigna, S., 2009. Psychology and economics: Evidence from the field. Journal of Economic Literature 47 (2), 315–72.
http://ideas.repec.org/a/aea/jeclit/v47y2009i2p315-72.html

Diener, E., 2000. Subjective well-being: The science of happiness and a proposal for a national index. American Psychologist 55 (1), 34–43.

Diener, E., Suh, E. M., Lucas, R. E., Smith, H. L., 1999. Subjective well-being: Three decades of progress. Psychological Bulletin 125 (2), 276–302.

Dietz, T., Ostrom, E., Stern, P. C., 2003. The struggle to govern the commons. Science 302 (5652), 1907–1912, PMID: 14671286.
http://www.sciencemag.org/content/302/5652/1907

Dornburg, V., Vuuren, D. v., Ven, G. v. d., Langeveld, H., Meeusen, M., Banse, M., Oorschot, M. v., Ros, J., Born, G. J. v. d., Aiking, H., Londo, M., Mozaffarian, H., Verweij, P., Lysen, E., Faaij, A., Mar. 2010. Bioenergy revisited: Key factors in global potentials of bioenergy. Energy & Environmental Science 3 (3), 258–267.
http://pubs.rsc.org/en/content/articlelanding/2010/ee/b922422j

Easterlin, R. A., 2006. Life cycle happiness and its sources: Intersections of psychology, economics, and demography. Journal of Economic Psychology 27 (4), 463–482.
http://www.sciencedirect.com/science/article/pii/S0167487006000407

Fargione, J., Hill, J., Tilman, D., Polasky, S., Hawthorne, P., Feb. 2008. Land clearing and the biofuel carbon debt. Science 319 (5867), 1235–1238, PMID: 18258862.
http://www.sciencemag.org/content/319/5867/1235

Fehr, E., Fischbacher, U., 2002. Why social preferences matter – the impact of non-selfish motives on competition, cooperation and incentives. The Economic Journal 112 (478), C1–C33.
http://onlinelibrary.wiley.com/doi/10.1111/1468-0297.00027/abstract

Fehr, E., Gächter, S., 2000. Fairness and retaliation: The economics of reciprocity. The Journal of Economic Perspectives 14 (3), 159–181, ArticleType: research-article / Full publication date: Summer, 2000 / Copyright © 2000 American Economic Association.
http://www.jstor.org/stable/2646924

Fehr, E., Gächter, S., Jan. 2002. Altruistic punishment in humans. Nature 415 (6868), 137–140.
http://www.nature.com/nature/journal/v415/n6868/abs/415137a.html

Fehr, E., Rockenbach, B., 2003. Detrimental effects of sanctions on human altruism. Nature 422 (6928), 137–140.
http://www.nature.com/nature/journal/v422/n6928/abs/nature01474.html

Fehr, E., Schmidt, K. M., 1999. A theory of fairness, competition, and cooperation. The Quarterly Journal of Economics 114 (3), 817–868.
http://qje.oxfordjournals.org/content/114/3/817

Fernandes, C., Frías, P., Latorre, J. M., Aug. 2012. Impact of vehicle-to-grid on power system operation costs: The spanish case study. Applied Energy 96, 194–202.
http://www.sciencedirect.com/science/article/pii/S0306261911007641

Frey, B. S., Jegen, R., 2001. Motivation crowding theory. Journal of Economic Surveys 15 (5), 589–611.
http://onlinelibrary.wiley.com/doi/10.1111/1467-6419.00150/abstract

Frey, B. S., Stutzer, A., 2002. What can economists learn from happiness research? Journal of Economic Literature 40 (2), 402–435.
http://www.jstor.org/stable/2698383

Fudenberg, D., 2006. Advancing beyond "Advances in behavioral economics". Journal of Economic Literature 44 (3), 694–711, ArticleType: research-article / Full publication date: Sep., 2006 / Copyright © 2006 American Economic Association.
http://www.jstor.org/stable/30032349

Gigerenzer, G., Selten, R., 2002. Bounded Rationality: The Adaptive Toolbox. MIT Press.

Gintis, H., Bowles, S., Boyd, R., Fehr, E., 2003. Explaining altruistic behavior in humans. Evolution and Human Behavior 24 (3), 153–172.
http://www.sciencedirect.com/science/article/pii/S1090513802001575

Girod, B., van Vuuren, D. P., de Vries, B., Apr. 2013. Influence of travel behavior on global CO2 emissions. Transportation Research Part A: Policy and Practice 50, 183–197.
http://www.sciencedirect.com/science/article/pii/S0965856413000694

Gneezy, U., List, J. A., 2006. Putting behavioral economics to work: Testing for gift exchange in labor markets using field experiments. Econometrica 74 (5), 1365–1384.
http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0262.2006.00707.x/abstract

Gul, F., Pesendorfer, W., 2001. Temptation and self-control. Econometrica 69 (6), 1403–1435.
http://onlinelibrary.wiley.com/doi/10.1111/1468-0262.00252/abstract

Hedegaard, K., Mathiesen, B. V., Lund, H., Heiselberg, P., Nov. 2012a. Wind power integration using individual heat pumps – analysis of different heat storage options. Energy 47 (1), 284–293.
http://www.sciencedirect.com/science/article/pii/S0360544212007086

Hedegaard, K., Ravn, H., Juul, N., Meibom, P., Dec. 2012b. Effects of electric vehicles on power systems in northern europe. Energy 48 (1), 356–368.
http://www.sciencedirect.com/science/article/pii/S036054421200463X

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., May 2001. In search of homo economicus: Behavioral experiments in 15 small-scale societies. The American Economic Review 91 (2), 73–78, ArticleType: research-article / Issue Title: Papers and Proceedings of the Hundred Thirteenth Annual Meeting of the American Economic Association / Full publication date: May, 2001 / Copyright © 2001 American Economic Association.
http://www.jstor.org/stable/2677736

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., McElreath, R., Alvard, M., Barr, A., Ensminger, J., 2005. " economic man" in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. Behavioral and brain sciences 28 (6), 795–814.
http://journals.cambridge.org/production/action/cjoGetFulltext?fulltextid=364679

Hepburn, C., Duncan, S., Papachristodoulou, A., Jun. 2010. Behavioural economics, hyperbolic discounting and environmental policy. Environmental and Resource Economics 46 (2), 189–206.
http://link.springer.com/article/10.1007/s10640-010-9354-9

Hoch, S. J., Ha, Y.-W., 1986. Consumer learning: Advertising and the ambiguity of product experience. Journal of Consumer Research 13 (2), 221–233.
http://www.jstor.org/stable/2489228

Hoch, S. J., Loewenstein, G. F., 1991. Time-inconsistent preferences and consumer self-control. Journal of Consumer Research 17 (4), 492–507.
http://www.jstor.org/stable/2626842

Hodgson, G. M., Mar. 1998. The approach of institutional economics. Journal of Economic Literature 36 (1), 166–192.
http://www.jstor.org/stable/2564954

Hodgson, G. M., 2003. The hidden persuaders: institutions and individuals in economic theory. Cambridge Journal of Economics 27 (2), 159–175.
http://cje.oxfordjournals.org/content/27/2/159

Jakob, M., Steckel, J. C., Flachsland, C., Baumstark, L., 2012. Climate finance for developing country mitigation: Blessing or curse? Potsdam Institute for Climate Impact Research Working Paper, Potsdam. http://www. pik potsdam. de/members/steckel/publications/climatefinacecurseorblessing.
http://www.pik-potsdam.de/members/jakob/publications/jakob-et-al-climate-finance-curse-or-blessing.pdf

Jones, C. I., Romer, P. M., Jan. 2010. The new kaldor facts: Ideas, institutions, population, and human capital. American Economic Journal: Macroeconomics 2 (1), 224–245.
http://www.aeaweb.org/articles.php?doi=10.1257/mac.2.1.224

Kahneman, D., 2003a. Maps of bounded rationality: Psychology for behavioral economics. The American Economic Review 93 (5), 1449–1475.
http://www.jstor.org/stable/3132137

Kahneman, D., 2003b. A psychological perspective on economics. The American Economic Review 93 (2), 162–168, ArticleType: research-article / Issue Title: Papers and Proceedings of the One Hundred Fifteenth Annual Meeting of the American Economic Association, Washington, DC, January 3-5, 2003 / Full publication date: May, 2003 / Copyright © 2003 American Economic Association.
http://www.jstor.org/stable/3132218

Kahneman, D., 2011. Thinking, Fast and Slow. Macmillan.

Kahneman, D., Diener, E., Schwarz, N., 2003. Well-Being: Foundations of Hedonic Psychology. Russell Sage Foundation.

Kahneman, D., Knetsch, J. L., Thaler, R. H., 1986a. Fairness and the assumptions of economics. Journal of business, S285–S300.
http://www.jstor.org/stable/10.2307/2352761

Kahneman, D., Knetsch, J. L., Thaler, R. H., Sep. 1986b. Fairness as a constraint on profit seeking: Entitlements in the market. The American Economic Review 76 (4), 728–741.
http://www.jstor.org/stable/1806070

Kahrl, F., Roland-Holst, D., Jan. 2010. Welfare and equity implications of commercial biofuel. In: Khanna, M., Scheffran, J., Zilberman, D. (Eds.), Handbook of Bioenergy Economics and Policy. No. 33 in Natural Resource Management and Policy. Springer New York, pp. 385–400.
http://link.springer.com/chapter/10.1007/978-1-4419-0369-3_22

Kiviluoma, J., Meibom, P., Mar. 2010. Influence of wind power, plug-in electric vehicles, and heat storages on power system investments. Energy 35 (3), 1244–1255.
http://www.sciencedirect.com/science/article/pii/S0360544209004782

Klein, D., Luderer, G., Kriegler, E., Strefler, J., Bauer, N., Leimbach, M., Popp, A., Dietrich, J. P., Humpenöder, F., Lotze-Campen, H., Edenhofer, O., 2014. The value of bioenergy in low stabilization scenarios: an assessment using REMIND-MAgPIE. Climatic Change, 1–14.
http://link.springer.com/article/10.1007/s10584-013-0940-z

Kloprogge, P., Sluijs, J. P. V. D., Apr. 2006. The inclusion of stakeholder knowledge and perspectives in integrated assessment of climate change. Climatic Change 75 (3), 359–389.
http://link.springer.com/article/10.1007/s10584-006-0362-2

Knopf, B., Edenhofer, O., Flachsland, C., Kok, M. T., Lotze-Campen, H., Luderer, G., Popp, A., van Vuuren, D. P., 2010. Managing the low-carbon Transition—From model results to policies. The Energy Journal 31 (special issue 1), 223–245.
ftp://ftp.elet.polimi.it/users/Marino.Gatto/ASPCourse2010/PolyGame/Knopf_Policy_Energyjournal2010.pdf

Krey, V., O'Neill, B. C., van Ruijven, B., Chaturvedi, V., Daioglou, V., Eom, J., Jiang, L., Nagai, Y., Pachauri, S., Ren, X., Dec. 2012. Urban and rural energy use and carbon dioxide emissions in asia. Energy Economics 34, Supplement 3, S272–S283.
http://www.sciencedirect.com/science/article/pii/S0140988312000904

Krueger, T., Page, T., Hubacek, K., Smith, L., Hiscock, K., Oct. 2012. The role of expert opinion in environmental modelling. Environmental Modelling & Software 36, 4–18.
http://www.sciencedirect.com/science/article/pii/S136481521200028X

Laibson, D., 1997. Golden eggs and hyperbolic discounting. The Quarterly Journal of Economics 112 (2), 443–478.
http://qje.oxfordjournals.org/content/112/2/443

Layard, R., 2006. Happiness and public policy: a challenge to the profession*. The Economic Journal 116 (510), C24–C33.
http://onlinelibrary.wiley.com/doi/10.1111/j.1468-0297.2006.01073.x/abstract

Lehmann, P., Creutzig, F., Ehlers, M.-H., Friedrichsen, N., Heuson, C., Hirth, L., Pietzcker, R., Feb. 2012. Carbon lock-out: Advancing renewable energy policy in europe. Energies 5 (12), 323–354.
http://www.mdpi.com/1996-1073/5/2/323

Levine, D. K., 1998. Modeling altruism and spitefulness in experiments. Review of Economic Dynamics 1 (3), 593–622.
http://www.sciencedirect.com/science/article/pii/S1094202598900230

Luderer, G., Bosetti, V., Jakob, M., Leimbach, M., Steckel, J., Waisman, H., Edenhofer, O., 2011. The economics of decarbonizing the energy system—results and insights from the RECIPE model intercomparison. Climatic Change, 1–29.
http://www.springerlink.com/content/g04377m307g03725/abstract/

Luderer, G., Leimbach, M., Bauer, N., Aboumahboub, T., Curras, T. A., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Mouratiadou, I., Pietzcker, R., Piontek, F., Roming, N., Schultes, A., Schwanitz, V. J., Strefler, J., Aug. 2013. Description of the REMIND model (version 1.5). SSRN Scholarly Paper ID 2312844, Social Science Research Network, Rochester, NY.
http://papers.ssrn.com/abstract=2312844

Lund, H., Möller, B., Mathiesen, B., Dyrelund, A., Mar. 2010. The role of district heating in future renewable energy systems. Energy 35 (3), 1381–1390.
http://www.sciencedirect.com/science/article/pii/S036054420900512X

Mathiesen, B. V., Duić, N., Stadler, I., Rizzo, G., Guzović, Z., Dec. 2012. The interaction between intermittent renewable energy and the electricity, heating and transport sectors. Energy 48 (1), 2–4.
http://www.sciencedirect.com/science/article/pii/S036054421200758X

Melillo, J. M., Reilly, J. M., Kicklighter, D. W., Gurgel, A. C., Cronin, T. W., Paltsev, S., Felzer, B. S., Wang, X., Sokolov, A. P., Schlosser, C. A., Dec. 2009. Indirect emissions

from biofuels: How important? Science 326 (5958), 1397–1399, PMID: 19933101.
http://www.sciencemag.org/content/326/5958/1397

Muraven, M., Baumeister, R. F., 2000. Self-regulation and depletion of limited resources: Does self-control resemble a muscle? Psychological Bulletin 126 (2), 247–259.

Ostrom, E., 1990. Governing the commons: The evolution of institutions for collective action. Cambridge university press.

Ostrom, E., 2009. Understanding institutional diversity. Princeton University Press.

Ostrom, E., Burger, J., Field, C. B., Norgaard, R. B., Policansky, D., 1999. Revisiting the commons: Local lessons, global challenges. Science 284 (5412), 278–282, PMID: 10195886.
http://www.sciencemag.org/content/284/5412/278

Ostrom, E., Janssen, M. A., Anderies, J. M., 2007. Going beyond panaceas. Proceedings of the National Academy of Sciences 104 (39), 15176–15178, PMID: 17881583.
http://www.pnas.org/content/104/39/15176

Parker, P., Letcher, R., Jakeman, A., Beck, M., Harris, G., Argent, R., Hare, M., Pahl-Wostl, C., Voinov, A., Janssen, M., Sullivan, P., Scoccimarro, M., Friend, A., Sonnenshein, M., Barker, D., Matejicek, L., Odulaja, D., Deadman, P., Lim, K., Larocque, G., Tarikhi, P., Fletcher, C., Put, A., Maxwell, T., Charles, A., Breeze, H., Nakatani, N., Mudgal, S., Naito, W., Osidele, O., Eriksson, I., Kautsky, U., Kautsky, E., Naeslund, B., Kumblad, L., Park, R., Maltagliati, S., Girardin, P., Rizzoli, A., Mauriello, D., Hoch, R., Pelletier, D., Reilly, J., Olafsdottir, R., Bin, S., 2002. Progress in integrated assessment and modelling. Environmental Modelling & Software 17 (3), 209–217.
http://www.sciencedirect.com/science/article/pii/S1364815201000597

Phelps, E., Pollak, R., Apr. 1968. On second-best national saving game-equilibrium growth. Review of Economic Studies 35 (2), 185.
http://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=4619008&site=ehost-live

Popp, A., Rose, S. K., Calvin, K., Vuuren, D. P. V., Dietrich, J. P., Wise, M., Stehfest, E., Humpenöder, F., Kyle, P., Vliet, J. V., Bauer, N., Lotze-Campen, H., Klein, D., Kriegler, E., 2014. Land-use transition for bioenergy and climate stabilization: model comparison of drivers, impacts and interactions with other land use based mitigation options. Climatic Change, 1–15.
http://link.springer.com/article/10.1007/s10584-013-0926-x

Rabin, M., 1993. Incorporating fairness into game theory and economics. The American Economic Review 83 (5), 1281–1302.
http://www.jstor.org/stable/2117561

Rabl, A., Jun. 1996. Discounting of long-term costs: What would future generations prefer us to do? Ecological Economics 17 (3), 137–145.
http://www.sciencedirect.com/science/article/pii/S0921800996800024

Raskin, P. D., Apr. 2008. World lines: A framework for exploring global pathways. Ecological Economics 65 (3), 461–470.
http://www.sciencedirect.com/science/article/pii/S0921800908000700

Raskin, P. D., Electris, C., Rosen, R. A., Aug. 2010. The century ahead: Searching for. Sustainability 2 (8), 2626–2651.
http://www.mdpi.com/2071-1050/2/8/2626

Risbey, J., Kandlikar, M., Patwardhan, A., Nov. 1996. Assessing integrated assessments. Climatic Change 34 (3-4), 369–395.
http://link.springer.com/article/10.1007/BF00139298

Risbey, J., Sluijs, J. v. d., Kloprogge, P., Ravetz, J., Funtowicz, S., Quintana, S. C., Mar. 2005. Application of a checklist for quality assistance in environmental modelling to an energy model. Environmental Modeling & Assessment 10 (1), 63–79.
http://link.springer.com/article/10.1007/s10666-004-4267-z

Robeyns, I., 2005. The capability approach: a theoretical survey. Journal of human development 6 (1), 93–117.
http://www.tandfonline.com/doi/abs/10.1080/146498805200034266

Roemer, J. E., Mar. 2011. The ethics of intertemporal distribution in a warming planet. Environmental and Resource Economics 48 (3), 363–390.
http://link.springer.com/article/10.1007/s10640-010-9414-1

Rose, S. K., Kriegler, E., Bibas, R., Calvin, K., Popp, A., Vuuren, D. P. v., Weyant, J., 2014. Bioenergy in energy transformation and climate management. Climatic Change, 1–17.
http://link.springer.com/article/10.1007/s10584-013-0965-3

Rosen, R. A., Electris, C., Raskin, P. D., 2010. Global scenarios for the century ahead. Tellus Institute, 1–21.
http://sallan.org/pdf-docs/TELLUS_21Century.pdf

Rozendaal, E., Buijzen, M., Valkenburg, P., 2009. Do children's cognitive advertising defenses reduce their desire for advertised products? Communications 34 (3), 287–303.
http://www.degruyter.com/view/j/comm.2009.34.issue-3/comm.2009.018/comm.2009.018.xml

Sagar, A. D., Kartha, S., 2007. Bioenergy and sustainable development? Annual Review of Environment and Resources 32 (1), 131–167.
http://www.annualreviews.org/doi/abs/10.1146/annurev.energy.32.062706.132042

Schafer, A., 2012. Introducing behavioral change in transportation into energy/economy/environment models. World Bank Policy Research Working Paper (6234).
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2162802

Schelling, T. C., Apr. 1995. Intergenerational discounting. Energy Policy 23 (4–5), 395–401.
http://www.sciencedirect.com/science/article/pii/0301421595901643

Schmid, E., 2013. On the exploration of german mitigation scenarios. Ph.D. thesis, Technische Universität Berlin, Berlin, Germany.
http://opus4.kobv.de/opus4-tuberlin/frontdoor/index/index/docId/1784

Schneider, S. H., Dec. 1997. Integrated assessment modeling of global climate change: Transparent rational tool for policy making or opaque screen hiding valueladen assumptions? Environmental Modeling & Assessment 2 (4), 229–249.
http://link.springer.com/article/10.1023/A%3A1019090117643

Schwanitz, V. J., Dec. 2013. Evaluating integrated assessment models of global climate change. Environmental Modelling & Software 50, 120–131.
http://www.sciencedirect.com/science/article/pii/S1364815213001965

Searchinger, T. D., Hamburg, S. P., Melillo, J., Chameides, W., Havlik, P., Kammen, D. M., Likens, G. E., Lubowski, R. N., Obersteiner, M., Oppenheimer, M., Robertson, G. P., Schlesinger, W. H., Tilman, G. D., Oct. 2009. Fixing a critical climate accounting error. Science 326 (5952), 527–528, PMID: 19900885.
http://www.sciencemag.org/content/326/5952/527

Sen, A., 1985a. Commodities and capabilities. Elsevier Science Publishers, Oxford.
http://ideas.repec.org/b/oxp/obooks/9780195650389.html

Sen, A., 1985b. Well-being, agency and freedom: the dewey lectures 1984. The Journal of Philosophy 82 (4), 169–221.
http://www.jstor.org/stable/10.2307/2026184

Sen, A., Nussbaum, M., 1993. Capability and well-being. The quality of life 1 (9), 30–54.
ftp://s208.math.msu.su/140000/7da6074f87dc25f820a25cb0a0cb87cd#page=25

Simon, H. A., 1982. Models of Bounded Rationality: Empirically grounded economic reason. MIT Press.

Stanton, E. A., Aug. 2011. Negishi welfare weights in integrated assessment models: the mathematics of global inequality. Climatic Change 107 (3-4), 417–432.
http://link.springer.com/article/10.1007/s10584-010-9967-6

Stephan, G., Müller-Fürstenberger, G., Previdoli, P., Jul. 1997. Overlapping generations or infinitely-lived agents: Intergenerational altruism and the economics of global warming. Environmental and Resource Economics 10 (1), 27–40.
http://link.springer.com/article/10.1023/A%3A1026479106896

Steward, D., Saur, G., Penev, M., Ramsden, T., 2009. Lifecycle cost analysis of hydrogen versus other technologies for electrical energy storage. Tech. Rep. Report No.: NREL/TP56046719, National Renewable Energy Laboratory, Golden (CO)(2009 Nov).
https://www.eere.energy.gov/hydrogenandfuelcells/pdfs/46719.pdf

Sumaila, U. R., Walters, C., Jan. 2005. Intergenerational discounting: a new intuitive approach. Ecological Economics 52 (2), 135–142.
http://www.sciencedirect.com/science/article/pii/S0921800904003003

Tella, R. D., MacCulloch, R. J., Oswald, A. J., 2003. The macroeconomics of happiness. Review of Economics and Statistics 85 (4), 809–827.
http://dx.doi.org/10.1162/003465303772815745

Thaler, R., Benartzi, S., 2004. Save more tomorrow^{TM}: Using behavioral economics to increase employee saving. Journal of Political Economy 112 (S1), S164–S187, ArticleType: research-article / Issue Title: Papers in Honor of Sherwin Rosen: A Supplement to Volume 112 / Full publication date: February 2004 / Copyright © 2004 The University of Chicago Press.
http://www.jstor.org/stable/10.1086/380085

Thaler, R. H., Sunstein, C. R., 2008. Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.

van der Sluijs, J. P., Mar. 2002. A way out of the credibility crisis of models used in integrated environmental assessment. Futures 34 (2), 133–146.
http://www.sciencedirect.com/science/article/pii/S0016328701000519

van Ruijven, B. J., van Vuuren, D. P., de Vries, B. J. M., Isaac, M., van der Sluijs, J. P., Lucas, P. L., Balachandra, P., Dec. 2011. Model projections for household energy use in india. Energy Policy 39 (12), 7747–7761.
http://www.sciencedirect.com/science/article/pii/S0301421511007105

Van Vuuren, D. P., Edmonds, J., Smith, S. J., Calvin, K. V., Karas, J., Kainuma, M., Nakicenovic, N., Riahi, K., Ruijven, B. J. v., Swart, R., Thomson, A., Dec. 2010. What do near-term observations tell us about long-term developments in greenhouse gas emissions? Climatic Change 103 (3-4), 635–642.
http://link.springer.com/article/10.1007/s10584-010-9940-4

Voinov, A., Bousquet, F., Nov. 2010. Modelling with stakeholders. Environmental Modelling & Software 25 (11), 1268–1281.
http://www.sciencedirect.com/science/article/pii/S1364815210000538

Weyant, J. P., Aug. 2009. A perspective on integrated assessment. Climatic Change 95 (3-4), 317–323.
http://link.springer.com/article/10.1007/s10584-009-9612-4

Statement of Contributions

The five core chapters of this thesis (Chapters 2 to 6) were conceptually discussed between the author of this thesis and his principle advisor, Prof. Dr. Ottmar Edenhofer, as well as the direct supervisor, Dr. Gunnar Luderer. They are the result of collaborations with a number of colleagues at PIK and other research institutes, as indicated for each article. The author of this thesis has made extensive contributions to the contents of all five papers, from conceptual design, to numerical implementation, to writing. A summary of the contributions to specific chapters are listed below:

Chapter 2 Gunnar Luderer developed the method of calculating secondary energy based mitigation shares and wrote the major part of the article, with revisions and contributions by all other authors. Robert Pietzcker improved the REMIND version used for the article by implementing system integration costs, updating the resource potentials for renewables, and designing new final energy demand scenarios. RP produced the REMIND scenarios, and provided the supplementary material on energy accounting. Markus Haller contributed to the implementation of the REMIND model, wrote the post-processing tools for calculating the mitigation shares, and contributed to writing the methodological part of the article and the major part of the supplementary material. Nico Bauer contributed to the development of the model version used in the AME project, in particular the fossil fuel extraction sector.

Chapter 3 Gunnar Luderer and Volker Krey developed the conceptual design of the article, performed much of the data analysis and wrote large parts of the article, with contributions and revisions from all co-authors. Robert Pietzcker produced the REMIND scenarios, assisted with the data analysis, and wrote large parts of the discussion on drivers of VRE deployment (Section 4). VK, Katherine Calvin, James Merrick, Silvana Mima, Jasper Van Vliet and Kenichi Wada supplied the scenario results for MESSAGE, GCAM, MERGE, POLES, IMAGE, and DNE21+.

Chapter 4 Robert Pietzcker conceived the main research questions and wrote the article. He is solely responsible for developing and implementing the representation of system integration costs in REMIND, performing the scenario runs and carrying out the data analysis. Susanne Manger developed the idea for the land use competition framework and contributed to the writing of a previous version of the article. Daniel Stetter provided the input to calculate the solar resource potential data. Gunnar Luderer assisted with the interpretation of results, critically reviewed all aspects of the paper and contributed in extensive discussions.

Chapter 5 Robert Pietzcker conceived the main research questions and wrote the article. He implemented an improved transport module in REMIND, produced the REMIND scenario runs, and performed the data analysis and interpretation of results. Thomas Longden contributed to writing Section 3 of the article and helped framing the results. Scenario results for CHN-T, GCAM, PECE and WITCH-T were provided by

Chen Wenying, Page Kyle, Fu Sha, and TL. Gunnar Luderer and Elmar Kriegler assisted with the interpretation of results and gave valuable feedback.

Chapter 6 The core research question was conceived by Gunnar Luderer. The scenario design was developed by GL, Robert Pietzcker, Elmar Kriegler, and Christoph Bertram. Both model improvement and calculation of the actual scenario ensembles were performed by CB and RP. Malte Meinshausen calculated the climate response to the emissions from the REMIND scenarios using a probabilistic climate model. GL did most of the data analysis, with contributions from RP and CB. GL wrote the paper with contributions and revisions from all co-authors.

Tools and Resources

This dissertation relies heavily on numerical modeling. Naturally, a number of software tools were used to create and run the models, and to process, analyze and visualize the results. This section lists these tools.

Modeling The REMIND modeling framework was implemented in GAMS[3]. The CONOPT3[4] solver was used to solve the non-linear optimization. All code projects were managed using the Subversion version control system[5].

Data Processing For data pre- and postprocessing work, both MathWorks' MATLAB[6], version 7.5 (R2007b) and Microsoft Excel 2010[7] was used.

Typesetting This document was prepared using LaTeX 2ε[8], particularly the pdfpages package to include Chapters 2 to 6 in their given layouts. Chapters 2 to 6 were written with Microsoft Word 2010[9].

Literature management Zotero[10] was used for literature management.

[3] http://www.gams.com
[4] http://www.gams.com/docs/conopt3.pdf
[5] http://subversion.apache.org/
[6] http://www.mathworks.de/products/matlab/
[7] http://office.microsoft.com
[8] http://www.latex-project.org/intro.html
[9] http://office.microsoft.com
[10] http://www.zotero.org/

Acknowledgements

Many people have been involved in this thesis in one way or another and I want to express my gratitude to everyone for continuing support, guidance and friendship.

First of all I want to thank Ottmar Edenhofer for providing the opportunity for this thesis and for all his support along the way. His openness to critique and discussions and his willingness to address and tackle any difficult issues led to a truly inspiring and cooperative atmosphere in the whole research domain. Should I ever lead a group of people myself, I know I will manage better thanks to his role model.

Special thanks goes to Gunnar Luderer, my supportive, encouraging, enthusiastic and inspiring supervisor and mentor. Be it traveling through China on horseback, struggling with REMIND results all night long after arriving at a conference hotel, or venting our frustration about modelers who just don't get the problems of CES functions – we spent many a day and night discussing both scientific problems and the world at large.

To my office mates: David Klein, who started with me on that long and winding road that finally led to our theses after some detours to the Fusion, Brandenburg and Tuscany. Christoph Bertram, for his endless patience with me ranting and babbling behind my screen, and his great sense of humor – sometimes slapstick, sometimes witty. Lion Hirth, who joined me in A51 – to fits of laughter and the 4pm mouse.

To Falko Ueckerdt, for really inspiring scientific work together, for sharing ups and downs and showing me a different perspective on the inner workings of this world in deep discussions at the top of various mountains. Eva Schmid for diligent and ruthless proofreading, and her way of openly communicating different views on various topics. Lavinia Baumstark, for lots of REMIND help and many a night's discussion when crashing at her place after a night of Tango in Potsdam.

More generally, to all my colleagues at PIK who made working there a very enjoyable experience – especially Sylvie Ludig, Markus Haller, Michael Lüken, Anastasis Giannousakis, Jessica Strefler, Jan Steckel, Michaja Pehl, Christian Flachsland, Kai Lessmann, Ulrike Kornek, Michael Jakob, Michael Pahle, Marian Leimbach, Nico Bauer, Elmar Kriegler and Brigitte Knopf.

I am grateful to Dorothe Ilskens, Nicole Reinhardt, Kristiyana Neumann and Laura Delsa, for their skills at organizing this bunch of chaotic scientists, and their endless patience and unfailing assistance whenever help was needed. I also want to mention Dietmar Gibietz-Rheinbay and Benjamin Kriemann for patiently answering all questions and inquiries regarding my computer.

And now to the (equally important) non-academic side of my life, i.e. the various people who kept me sane throughout the years and filled my life with sunshine and colors:

Veronika Bierbaum, who on that fateful day in Dresden convinced me that writing a dissertation might be a reasonable next step after leaving consulting. Besides being great

company and sharing everything and more over the last fifteen years, she always helped to put myself into perspective when I lost touch with what is important in life.

My roommates and friends Lena, Vera, Fritz, Jana, Erik, Astrid, Wibke, Peter and Simon, who took me on a pirate ship to Copenhagen to sink a coal plant and save the world – the first we achieved, the second not yet. Their warmth made Berlin my home and the Mali a place to rest my soul. Thank you for enduring my continuous excuse of having a project zombieline crawling in the near future!

A word of deep gratitude to Tango Argentino – that sublime dance, which filled my Sundays at the Tangoloft with bliss, which offered me a new connection to the world and a way to find and express my creativity.

My parents and my whole family, for always supporting and believing in me, which has helped me to overcome the difficulties in life – in general and with this thesis in particular – more than once.

The last word is dedicated to Niki, who was there throughout these long years, and who continuously fills my life with love and laughter.