Land-based climate change mitigation: modeling bioenergy production, afforestation and avoidance of deforestation

vorgelegt von
Florian Humpenöder
M.A. Nachhaltiges Wirtschaften
geboren in Roth

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Promotionsausschuss:

Vorsitzende: Prof. Dr. Birgit Kleinschmit
Gutachter: Prof. Dr. Ottmar Edenhofer
Gutachter: Prof. Dr. Hermann Lotze-Campen

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Summary

Global food demand is projected to increase in the coming decades due to a growing and more affluent world population. In addition to agriculture, ambitious climate targets could further increase anthropogenic land-use in the course of the 21st century. Currently, bioenergy use in combination with Carbon Capture and Storage (CCS), afforestation and avoidance of deforestation are the most discussed land-based mitigation options. To evaluate these land-based options, it is crucial to investigate their mitigation potential and land requirement under consideration of interactions with the traditional agricultural sector. For instance, land-based mitigation might compete for land with food crop production, which could trigger investments in agricultural R&D targeted at yield increases.

Thus, the overarching research question of this thesis is: *What is the global potential of land-based carbon mitigation in the 21st century, what are the associated land requirements and what are the implications for the agricultural sector?* The overarching research question is subdivided into five specific research questions: (1) What is the carbon mitigation potential of global forest and land-use protection schemes? (2) How much bioenergy can be supplied at what price, with and w/o GHG emissions pricing in the land system? (3) How does irrigation in bioenergy production affect land and water resources, and what are the impacts on bioenergy prices? (4) How much land do afforestation and bioenergy with CCS require for how much carbon dioxide removal (CDR) from the atmosphere? (5) What are the direct and indirect effects of moderate climate change on terrestrial carbon stocks and what are the implications for land-based carbon mitigation?

To answer these research questions, this thesis employs methods of model-based computer simulation and scenario analysis. Central to this thesis is the Model of Agricultural Production and its Impacts on the Environment (MAgPIE), a spatially explicit economic land-use model with global coverage for simulations up to the year 2100. MAgPIE optimizes land-use patterns with the objective of minimizing global agricultural production costs and calculates the associated GHG emissions. Furthermore, MAgPIE derives economic indicators, e.g. bioenergy prices. The model simulations are subject to socio-economic assumptions, such as future food demand, and climate policy assumptions, such as bioenergy demand and GHG prices. Under carbon pricing, the model features endogenous abatement of carbon dioxide (CO_2) emissions through reduced deforestation. For this thesis, the existing model has been extended by large-scale afforestation as option for CDR.

(1) The MAgPIE results indicate that a price on CO_2 emissions from deforestation substantially reduces land-use change emissions. However, due to partial displacement of agricultural expansion to non-forest land types, land-use change emissions are still considerable. More comprehensive land-use protection schemes can further reduce land-use change emissions, but require larger productivity increases in the agricultural sector. (2) Without GHG emissions pricing, supply prices for modern bioenergy increase almost linearly with bioenergy demand. This relationship becomes non-linear under GHG emissions pricing in the land system since the price on CO_2 emissions reduces the availability of forests for agricultural expansion. (3) Prohibition of irrigated bioenergy production can avoid additional pressure on global blue water resources, but considerably increases land requirements for bioenergy production, which is reflected in higher bioenergy supply prices. (4) The cumulative CDR per unit area from bioenergy use with CCS is 4-5 times higher compared to large-scale afforestation, since one unit of land can be used several times for bioenergy

production but just once for afforestation. However, bioenergy with CCS is only cost-effective at relatively high carbon prices. (5) Moderate climate change (RCP2.6) has beneficial effects on global agricultural yields, which reduces agricultural land requirements and in consequence deforestation. Thus, direct climate impacts on agricultural yields indirectly affect the terrestrial carbon balance. However, such beneficial climate impacts on terrestrial carbon stocks only marginally increase the potential of land-based carbon mitigation since the potential is already large without further climate change.

Zusammenfassung

Die weltweite Nahrungsmittelnachfrage wird in den kommenden Jahrzehnten aufgrund einer wachsenden und zugleich wohlhabenderen Weltbevölkerung voraussichtlich steigen. Neben der Landwirtschaft könnten im Verlauf des 21. Jahrhunderts ambitionierte Klimaschutzziele die Landnutzung durch den Menschen weiter erhöhen. Bioenergienutzung in Kombination mit Kohlenstoffabschneidung (CCS), Aufforstung und Vermeidung von Entwaldung sind die derzeit am stärksten diskutierten landbezogenen Klimaschutzmaßnahmen. Um diese landbezogenen Maßnahmen bewerten zu können, ist es entscheidend deren Minderungspotenzial und Flächenbedarf unter Berücksichtigung von Interaktionen mit dem traditionellen Agrarsektor zu untersuchen. Zum Beispiel könnten landbezogene Klimaschutzmaßnahmen mit der Nahrungsmittelproduktion um Land konkurrieren und somit Anreize für verstärkte Investitionen in die Agrarforschung zur Ertragserhöhung schaffen.

Daher lautet die übergeordnete Fragestellung dieser Dissertation: *Wie groß ist das globale Potenzial von landbezogener Kohlenstoff-Emissionsminderung im 21. Jahrhundert, wie groß ist der damit einhergehende Flächenbedarf und was sind die Auswirkungen auf den Agrarsektor?* Die übergeordnete Fragestellung ist in fünf spezifische Forschungsfragen untergliedert: (1) Was können globale Wald- und Landschutzprogramme zur Minderung von Kohlenstoff-Emissionen beitragen? (2) Wie viel Bioenergie kann zu welchem Preis angeboten werden, mit und ohne Bepreisung von Treibhausgas-Emissionen aus der Landnutzung? (3) Wie beeinflusst Bewässerung in der Bioenergieproduktion Land- und Wasserressourcen und was sind die Auswirkungen auf Bioenergiepreise? (4) Welches Land wird für Aufforstung und Bioenergienutzung mit CCS für welche Kohlenstoffdioxidentfernung aus der Atmosphäre benötigt? (5) Welche direkten und indirekten Effekte hat moderater Klimawandel auf terrestrische Kohlenstoffspeicher und was sind die Konsequenzen für landbezogene Kohlenstoff-Emissionsminderung?

Um diese Forschungsfragen zu beantworten, verwendet diese Dissertation Methoden der modellbasierten Computersimulation und Szenarienanalyse. Von zentraler Bedeutung ist dabei das Modell MAgPIE (Model of Agricultural Production and its Impacts on the Environment), ein räumlich explizites ökonomisches Landnutzungsmodell mit globaler Abdeckung für Simulationen bis zum Jahr 2100. MAgPIE optimiert Landnutzungsmuster mit dem Ziel die globalen landwirtschaftlichen Produktionskosten zu minimieren und berechnet die damit einhergehenden Treibhausgas-Emissionen. Darüber hinaus ermittelt MAgPIE ökonomische Indikatoren, wie z.B. Bioenergiepreise. Die Modellsimulationen unterliegen sozio-ökonomischen Annahmen wie der zukünftigen Nahrungsmittelnachfrage, und Annahmen zur Klimapolitik wie Bioenergienachfrage und Treibhausgaspreise. Bei der Bepreisung von Emissionen kann das Modell endogen Kohlenstoffdioxid-Emissionen (CO_2) aus Entwaldung verringern. Für diese Dissertation wurde das existierende Modell um großskalige Aufforstung als Option zur Kohlenstoffdioxidentfernung erweitert.

(1) Die MAgPIE-Ergebnisse zeigen, dass die Bepreisung von CO_2-Emissionen aus Entwaldung Landnutzungsänderungen und damit verbundene CO_2-Emissionen substanziell verringern kann. Allerdings sind die Emissionen aus Landnutzungsänderungen immer noch beträchtlich, da die landwirtschaftliche Expansion teilweise auf andere Landtypen als Wald verlagert wird.

Umfangreichere Landschutzprogramme können die Emissionen aus Landnutzungsänderungen weiter reduzieren, erfordern jedoch höhere Produktivitätssteigerungen im Agrarsektor. (2) Ohne Bepreisung von Treibhausgas-Emissionen steigen die Angebotspreise für moderne Bioenergie annährend linear mit der Bioenergienachfrage. Bei Bepreisung von Treibhausgas-Emissionen aus der Landnutzung wird dieser Zusammenhang nichtlinear, da der Preis auf CO_2-Emissionen die Verfügbarkeit von Wäldern für die landwirtschaftliche Expansion verringert. (3) Ein Verbot von bewässerter Bioenergieproduktion kann zusätzlichen Druck auf die globalen Wasserressourcen in Flüssen und Seen verringern, erhöht jedoch den Flächenbedarf für Bioenergieproduktion beträchtlich, was sich in höheren Angebotspreisen für Bioenergie widerspiegelt. (4) Das kumulative Potenzial für Kohlenstoffdioxidentfernung pro Flächeneinheit ist bei Bioenergienutzung mit CCS etwa 4 bis 5 Mal höher als bei großskaliger Aufforstung, da ein Stück Land mehrmals für Bioenergieproduktion, aber nur einmal für Aufforstung benutzt werden kann. Allerdings ist Bioenergienutzung mit CCS nur bei relativ hohen CO_2-Preisen kosteneffizient. (5) Moderater Klimawandel (RCP2.6) ist vorteilhaft für die globalen landwirtschaftlichen Erträge, was den landwirtschaftlichen Flächenbedarf und somit die Entwaldung verringert. Daher haben direkte Klimawirkungen auf landwirtschaftliche Erträge indirekte Effekte auf die terrestrische Kohlenstoffbilanz. Allerdings erhöhen solche vorteilhaften Klimawirkungen auf terrestrische Kohlenstoffspeicher das Potenzial von landbezogener Kohlenstoff-Emissionsminderung nur marginal, da das Potenzial bereits ohne weiteren Klimawandel groß ist.

I Introduction

1 Background

1.1 Global warming

According to the Fifth Assessment Report of Working Group I of the Intergovernmental Panel on Climate Change (IPCC) it is "*virtually certain* that human influence has warmed the global climate system" (Stocker et al., 2013, p. 73). The global mean temperature increased by 0.78°C between the average of the 1850-1900 period and the 2003-2011 period. Global warming is caused by changes in the atmospheric concentration of greenhouse gases (GHGs). Carbon dioxide (CO_2) is the most important GHG triggering climate change, besides methane (CH_4) and nitrous oxide (N_2O). Fossil fuel use, cement production and land-use change (mainly deforestation) have emitted 555 GtC to the atmosphere between 1750 and 2011, and about half of them since 1970. Of these anthropogenic CO_2 emissions, the ocean has absorbed 155 GtC, leading to ocean acidification. Another 160 GtC have been sequestered in the terrestrial biosphere. The remaining 240 GtC accumulated in the atmosphere, resulting in an increase of the atmospheric CO_2 concentration from 278 ppm in 1750 to 391 ppm in 2011 (Stocker et al., 2013). The total GHG concentration in 2011 is estimated to be 430 ppm CO_2 equivalent (CO_2eq) (IPCC, 2014). Observed impacts of climate change on natural and human system are manifold and regionally different. The global mean sea level rose by 0.19 m in the period 1901-2010, mainly due to the increased volume of warmer water and run-off from melting glaciers and ice sheets. Crop yields decreased in many world regions, in particular in low- and mid-latitude regions, but increased in some high-latitude regions. Extreme events due to higher climate variability, such as heat waves, floods or droughts, had impacts on multiple economic sectors, infrastructure, settlement and human health in some world regions (Field et al., 2014). Without effective climate change mitigation, global mean temperature is projected to increase by 3.7-4.8°C until 2100 compared to pre-industrial levels (Edenhofer et al., 2014a). In general, global warming beyond current levels is projected to intensify already observed impacts, such as flooding of low-lying coastal zones due to sea level rise, risks to global and regional food security due to extreme events, and water scarcity in subtropical dry regions. Especially the agricultural sector is affected by climate change. Crop models project strong negative effects on crop yields for high emissions scenarios, in particular for developing countries (Rosenzweig et al., 2014). In consequence, food prices could rise by about 25% until 2050 (Lotze-Campen et al., 2014). Moreover, passing critical thresholds can lead to abrupt and irreversible changes in the earth system or in interlinked natural and human systems. The risks associated with such tipping points increase non-linearly with global warming (Field et al., 2014).

1.2 Climate change mitigation

The overall projected risks of climate change are substantially reduced if global warming can be limited to below 2°C compared to pre-industrial levels (Field et al., 2014). A likely chance to reach the 2°C target requires the stabilization of atmospheric GHG concentration levels at about 450 ppm (CO_2eq) by 2100. An atmospheric GHG concentration of 450 ppm CO_2eq in 2100 corresponds to a Representative Concentration Pathway (RCP) with a radiative forcing of 2.6 W/m^2 in 2100 (RCP2.6) (Edenhofer et al., 2014a). For consistency with the 2°C target, current anthropogenic GHG emissions need to decline globally by 41%-71% until 2050 and by 78%-118% until 2100 (Edenhofer et al., 2014a). Such deep cuts in GHG emissions to near zero in 2100 require a huge transformation of all economic sectors, such as electricity, industry, transport, buildings, and agriculture, forestry and other land use (AFOLU). Decarbonisation of the energy supply sector, which accounted for 35% of all anthropogenic GHG emissions in 2010, through a shift from fossil fuels towards renewables, such as solar and wind power, is a key requirement for low stabilization targets (Edenhofer et al., 2014a). Besides decarbonisation of energy supply, also reductions in final energy demand, e.g. through increased energy efficiency and behavioral changes, and a switch towards low-carbon energy carriers in energy end-uses, e.g. in the building, industry and transport sector, have a high potential for mitigating CO_2 emissions. The AFOLU sector accounted for 24% of all anthropogenic GHG emissions in 2010 (Edenhofer et al., 2014a). Agricultural non-CO_2 GHG emissions include N_2O emissions from fertilizer application and CH_4 emissions from livestock (enteric fermentation, manure management) and paddy rice production. Mitigation strategies for such agricultural land-use emissions include technical options on the supply side, such as improved animal waste management, as well as behavioral changes on the demand side, such as diets with less animal products (Popp et al., 2010). CO_2 emissions from land-use and land-cover change (LULCC) primarily originate from deforestation (Houghton et al., 2012). Reducing or avoiding deforestation is considered as highly cost-efficient mitigation option (Kindermann et al., 2008). Besides these measures to reduce CO_2 emissions, many low stabilization scenarios rely on land-based carbon dioxide removal (CDR) options, such as bioenergy use in combination with Carbon Capture and Storage (CCS) or afforestation (Edenhofer et al., 2014a). In current integrated assessment models (IAMs), the availability of dedicated bioenergy for use with CCS critically determines the challenges for ambitious climate protection, in particular in economic terms (Kriegler et al., 2014b). Therefore, the global land system potentially plays an important role for ambitious climate change mitigation in the future.

1.3 The global land system

"In 1700, nearly half of the terrestrial biosphere was wild, without human settlements or substantial land use. Most of the remainder was in a seminatural state (45%) having only minor use for agriculture and settlements. By 2000, the opposite was true, with the majority of the biosphere in agricultural and settled anthromes, less than 20% seminatural and only a quarter left wild."

(Ellis et al., 2010, p. 589)

1.3.1 Current state

The Earth's ice-free land surface consists of about 12,750 Mha (Foley et al., 2011). Today, croplands for food and feed production cover about 12% of the Earth's ice-free land surface (1530 Mha), while pastures for livestock grazing cover another 26 % (3380 Mha) (Foley et al., 2011; Ramankutty et al., 2008). In total, agriculture occupies about 38% of the Earth's ice-free land surface, "the largest use of land on the planet" (Foley et al., 2011, p. 337). In contrast, urban areas account for less than 1% of the global land surface (Seppelt et al., 2013). Forests cover 31% of the global land surface (FAO, 2010). Of the globally 4033 Mha forest, primary forests account for 36%, secondary forests for 57% and planted forests for 7%. Close to 1200 Mha of global forests are primarily used for the production of wood and non-wood forest products (e.g. animal hunting or honey production). Another 949 Mha have multiple purposes - often including wood production. About 460 Mha of global forests are protected (e.g. national parks or wildlife reservoirs). The remaining about 30% of the global land surface, which are not covered with agriculture, cites or forests, consist mainly of mountains, deserts and tundra (Foley et al., 2011).

1.3.2 Recent developments

Globally, croplands and pastures expanded on average by 7.7 Mha/yr in the 1985-2005 period (Foley et al., 2011). However, the net expansion at the global scale is a result of regionally quite different developments. While agriculture expanded into tropical forests in Africa and South America, agricultural land was abandoned in Europe. According to the forest resources assessment report (FAO, 2010) highest deforestation rates in the 2000s occurred in Africa (3.4 Mha/yr) and South America (4.0 Mha/yr), while forests expanded in Asia (2.2 Mha/yr) and Europe (0.7 Mha/yr) on abandoned land. In North and Central America, forest area was almost constant in the 2000s. Global deforestation rates declined in the last decades from 8.3 Mha/yr in the 1990s to 5.2 Mha/yr in the 2000s. Net CO_2 emissions from changes in forest area amount to 0.5 GtC/yr on average for the period 1990-2010 (FAO, 2010). CO_2 emissions from all LULCCs (including forests) are estimated at 1.14 GtC/yr for the period 1990-2009 (Houghton et al., 2012).

1.3.3 Agriculture and food security

"Land-based production provides the major biophysical basis for food security"
(Verburg et al., 2013, p. 494).

Today, 842 million people suffer from chronic hunger (not enough food for an active and healthy live) – 12% of the people in the world, the vast majority of them living in developing countries (FAO, 2013b). The prevalence of undernourishment declined in recent decades. In the 1990s, more than one billion people were undernourished – about 19% of the world population at that time. Food security has different dimension. Food availability relates to the supply side, i.e. the production of enough food. In principle, global food production provides enough calories for feeding the current world population – 2,770 kcal/person/day (Alexandratos et al., 2012; IAASTD, 2009; Pretty et al., 2010). However, "some 2.3 billion people live in countries with under 2,500 kcal, and some 0.5 billion in countries with less than 2,000 kcal, while at the other extreme some 1.9 billion are in countries consuming more than 3,000 kcal" (Alexandratos et al., 2012, p. 1). The main reason for these differences in food access, another crucial dimension of food security, is poverty (Alexandratos et al., 2012; FAO, 2013b). Although poverty rates strongly declined in recent decades, today still 1.2 billion people live on less then 1.25 $ per day (FAO, 2013b; UNDP, 2014). Moreover, only 62% of global crop production is directly used for human nutrition, while 35% are used for feeding animals (3% are used for bioenergy and other purposes) (Foley et al., 2011). Animal-based food production (meat and dairy products) is much less efficient than crop based food production. The average conversion efficiency is about 10%, i.e. producing one unit of animal matter requires about ten units of plant matter (Godfray et al., 2010). Thus, one unit of cropland can feed much more people if its crops are used directly for humans, instead of feeding animals for meat or dairy production. Currently, 75% of the total agricultural land (croplands and pastures) is devoted to animal production, either for growing feed crops or livestock grazing (Foley et al., 2011).

1.3.4 Environmental impacts of agriculture

"The environmental impacts of agriculture include those caused by expansion (when croplands and pastures extend into new areas, replacing natural ecosystems) and those caused by intensification (when existing lands are managed to be more productive, often through the use of irrigation, fertilizers, biocides and mechanization)."
(Foley et al., 2011, p. 338)

Agricultural land expansion

The depletion of natural ecosystems due to the expansion of agriculture into forests threatens biodiversity and other ecosystem services that directly contribute to human well-being, such as water purification, air quality regulation and stable climate through carbon storage (Crossman et al., 2013; Nagendra et al., 2013).

Carbon dioxide (CO_2) emissions from land-use change

More than 25% of primary forest have been cleared in the past 300 years, largely for expanding agricultural areas (Hurtt et al., 2011). Net emissions due to land-use change (mainly deforestation) accumulate to 180 GtC for the period 1750-2011 (Stocker et al., 2013). The net contribution of land-use changes to total anthropogenic CO_2 emissions are about 32% for the 1750-2011 period, 19-20% in the 1980s and 1990s, and 10-12% in the 2000s (Stocker et al., 2013). The declining fraction of land-use change emissions in total CO_2 emissions is mainly due to the strong rise in fossil fuel emissions since the 1950s and only marginally due to less deforestation in recent decades (Houghton et al., 2012; Stocker et al., 2013).

Land-use intensification

According to Foley et al. (2011), global average crop production increased by 28% in the period 1985-2005. Global cropland area, however, increased only by 2.4% between 1985 and 2005, suggesting that the increase in crop production mostly originates from land-use intensification, i.e. increases in crop yields. Although cropland area increased only by 2.4%, harvested area increased by 7% between 1985 and 2005, mainly due to enhanced multiple cropping and less crop failures. In total, global average crop yields increased by 20% between 1985 and 2005 when the increase in harvested land is accounted for. Thus, increases in global crop production in the last decades largely originate from land-use intensification and only little from land expansion.

Nitrous oxide (N_2O) emissions

In the last decades, increased synthetic fertilizer use substantially contributed to land-use intensification. Since the 1960s, nitrogen fertilizer use, facilitated by the Haber-Bosch process, increased 9 fold globally, while phosphorus use, another essential nutrient to raise crops, tripled (Sutton et al., 2013). The use of synthetic nitrogen fertilizer in agriculture is associated with increased N_2O emissions from soils (Bouwman et al., 2013). N_2O is among the most important GHGs causing global warming. Today, N_2O emissions from agriculture clearly dominate total anthropogenic N_2O emissions (Ciais et al., 2013). Without mitigation action, global N_2O emissions from agriculture are projected to increase by 71% until 2055, with N_2O

emissions from soils and manure management showing the strongest increase (Popp et al., 2010). Less demand for livestock products and technological mitigation options on the supply side, such better manure management and fertilizer application, could strongly reduce agricultural N_2O emissions until 2050.

In addition, current levels of synthetic fertilizer use (nitrogen and phosphor) lead to nutrient abundance in geochemical cycles – with potential detrimental effects on water and air quality, natural ecosystems and biodiversity (Sutton et al., 2013). Without mitigation action, global nitrogen pollution in 2050 can be expected to rise to 102-156% of current levels (Bodirsky et al., 2014). Mitigation options, such as waste reduction, diets with less animal products, and more efficient fertilization and livestock management, could reduce nitrogen pollution in 2050 to 36-76% of current levels.

Methane (CH_4) emissions

After CO_2, CH_4 is the second most important GHG causing global warming (Ciais et al., 2013). CH_4 is the product of anaerobic decomposition of organic material. Currently, agriculture is the major contributor to anthropogenic CH_4 emissions (Ciais et al., 2013; Karakurt et al., 2012). Without mitigation action, global CH_4 emissions from agriculture (mainly ruminant enteric fermentation and manure management) are expected to increase by 57% until 2055 (Popp et al., 2010). Less demand for livestock products and improved livestock management on the supply side could strongly reduce agricultural CH_4 emissions until 2055.

Water resources

Increased irrigation of croplands was another important contributor to higher crop yields in recent decades (Foley et al., 2011). Today, 20% of global cropland is irrigated (25% of harvested area) (Portmann et al., 2010; Rost et al., 2008). "The largest portion of human 'blue' water withdrawal and water consumption (withdrawal minus return flow to the river system) from rivers, lakes and aquifers is for the purpose of irrigation. Irrigation water use has been estimated to reach ~2,500 $km^3\ year^{-1}$ globally, which represents almost 70% of total human blue water use. Global agricultural blue water consumption, i.e., the amount of water that transpires productively through the crops or evaporates unproductively from soils, water bodies and vegetation canopies, amounts to ~90% of overall blue water consumption, equaling about 1,200–1,800 $km^3\ year^{-1}$ (Shiklomanov & Rodda, 2003; Vörösmarty et al., 2005)" (Rost et al., 2008, p. 1). In a global study, Hoekstra et al. (2012) find that in 201 out of 405 rivers basins severe water scarcity occurred in at least in one month of the year in the period 1996-2005, affecting 2.67 billion people. In addition, rain-fed agriculture is the largest consumer of green water (water infiltrated into the soil from precipitation) (Rost et al., 2008).

1.4 The future of human land use

1.4.1 Food production

Population increase

The current world population of about 7 billion people is likely to increase to 9 billion people until 2050, which suggests an annual growth rate of about 0.75%, down from 1.7% for the period 1963-2007 (Alexandratos et al., 2012). This decrease in population growth is reflected in projections of demand for agricultural products. Annual growth rates of demand for agricultural products are projected to decline to 1.1% in the coming decades until 2050, down from 2.2% in the last four decades (Alexandratos et al., 2012). However, an annual increase of 1.1% reflects about a doubling of demand for agricultural products in the next four decades.

Dietary changes

Besides population dynamics, changes in per capita income play a key role for future food demand (Alexandratos et al., 2012; IAASTD, 2009). According to conservative estimates of the World Bank, per capita incomes in 2050 are 1.8-fold the present ones (Alexandratos et al., 2012). In the past, developed countries have undergone a transition towards more livestock products, such as milk and meat, with increasing purchasing power (IAASTD, 2009). It is expected that developing countries will follow this pattern of dietary changes. Projections of future food production indicate that global meat production needs to grow faster than cereal production in the coming decades, largely driven by the transition of some developing countries towards western levels of meat consumption (Alexandratos et al., 2012; Valin et al., 2014). A transition toward more livestock products further increases the challenge for future agricultural production. First of all, livestock production is associated with substantial GHG emissions. Secondly, animal-based food production is much more resource intensive compared to crop-based food production (see section 1.3.3).

Climate change

A further challenge for future food production arises from unabated climate change (Easterling et al., 2007; Porter et al., 2014; Rosenzweig et al., 2014). Higher temperatures and less precipitation typically have negative impacts on crop yields, while higher atmospheric CO_2 concentrations stimulate photosynthesis in C3 crops (CO_2 fertilization) and enhance water use efficiency in all crops (Ainsworth & Long, 2005; Leakey et al., 2009; Lobell & Gourdji, 2012). The net effect on crop yields depends on the prevailing climatic conditions (Lobell & Gourdji, 2012). In higher latitudes, changes in temperature, precipitation and CO_2 concentration can have positive effects on crop yields under moderate climate change (RCP2.6) (Easterling et al., 2007; Porter et al., 2014; Rosenzweig et al., 2014). In contrary, crop yields in tropical regions are typically affected negatively, even under low levels of warming.

1.4.2 Bioenergy with CCS

Biological carbon sequestration and geological storage

Biomass contains energy in form of carbon, which is absorbed from the atmosphere during plant growth owing to photosynthesis. Due to its carbon content, bioenergy is a very flexible energy carrier that can be converted into many types of secondary energy, such as heat, electricity or fuel (Chum et al., 2011). Compared to other renewable energy sources, such as wind or solar, which require immediate consumption or conversion, processed biomass can be stored, traded and used when and where needed, similar to fossil fuels (Heinimö & Junginger, 2009). The conversion of biomass to secondary energy by combustion releases large parts of the originally absorbed carbon back to the atmosphere. The CCS technology, which is still unproven at industrial scale, aims to capture such carbon released during conversion and to store it underground (Bennaceur et al., 2008; Edenhofer et al., 2014a; Kriegler et al., 2013). Therefore, bioenergy use in combination with CCS allows for negative CO_2 emissions or rather CDR from the atmosphere (biological carbon sequestration and geological storage) (Tavoni & Socolow, 2013).

Land-use related GHG emissions

Bioenergy use is intrinsically linked to agriculture since the production of biomass requires cropland - unless biomass is derived from forest residues (Chum et al., 2011; Popp et al., 2014). Additional biomass production could cause land-use change emissions from deforestation for additional cropland expansion (Searchinger et al., 2008). If biomass production displaces food production to other countries, this could result in so-called indirect land-use change emissions from deforestation in these countries (Lapola et al., 2010). In the absence of bioenergy production, re-growth of natural vegetation on abandoned agricultural land could increase carbon stocks (Haberl et al., 2012). Therefore, bioenergy production might not only lead to additional CO_2 emissions from land-use change but might also hamper carbon sequestration from re-growing vegetation. Bioenergy production can also cause additional N_2O emissions due to increased fertilizer use. N_2O emissions from fertilizing bioenergy in particular gain importance under high deployment levels of bioenergy, as expected for the second half of the 21st century under ambitious climate protection (Popp et al., 2011b). Direct and indirect land-use change emissions, as well as hampered re-growth of vegetation and other emissions along the life cycle of bioenergy, such as additional N_2O emission from increased fertilizer use or carbon losses during processing, should be considered for the evaluation of carbon emission savings attributable to bioenergy use (Sathaye et al., 2011). The bioenergy carbon debt owing to land-use change emissions pays off over time since a once deforested area can be used several times for biomass cultivation (Fargione et al., 2008). How fast the bioenergy carbon debt pays off, critically depends on the type of feedstock used for bioenergy production. 2nd generation dedicated lignocellulosic bioenergy, such miscanthus or switch grass, feature considerable higher yields than 1st generation food-crop based bioenergy crops, such as maize, rapeseed or palm oil (Chum et al., 2011). The term *bioenergy* refers to 2nd generation bioenergy in this thesis, unless indicated otherwise.

Biomass potential and cost

The mitigation potential of bioenergy with CCS strongly depends on the availability of biomass (Azar et al., 2010; Edenhofer et al., 2014a; Kriegler et al., 2013; Kriegler et al., 2014b). In 2008, biomass accounted for about 10.2% (50.3 EJ/yr) of total global primary energy supply (Chum et al., 2011). However, about 80% of today's biomass is traditional biomass, used for cooking or heating. Only the remaining 20% are modern bioenergy, used for biofuel, electricity or biogas production. While traditional biomass is mostly derived from forests (trees, branches, residues), modern bioenergy mostly originates from agricultural residues or dedicated energy crops. The future global technical biomass potential for 2050 has been estimated in several studies by making assumption on biomass yields and the area available for biomass production: 190 EJ/yr (Haberl et al., 2013), 26-141 EJ/yr (Erb et al., 2012), 130-270 EJ/yr (Beringer et al., 2011), 160-270 EJ/yr (Haberl et al., 2010), 200-500 EJ/yr (Dornburg et al., 2010), 120-300 EJ/yr (van Vuuren et al., 2009). These studies assume that there is no competition for land between food and biomass production, i.e. biomass production in these studies is only possible on areas that are not needed for food production. Based on an expert review of the scientific literature, Chum et al (2011) estimate that the global technical biomass potential is 100-300 EJ/yr in 2050. According to Creutzig et al (2014), the scientific literature shows high/medium/low agreement that the global sustainable technical biomass potential is 100/100-300/>300 EJ/yr. For the economic potential, the costs for land, capital and labor associated with biomass production are considered additionally. Hoogwijk et al (2009) find that 130-270 EJ/yr of biomass may be produced at costs below 2$/GJ by 2050 globally. Using the same approach, Van Vuuren et al (2009) estimate bioenergy production costs for 130 EJ/yr in 2050 of about 4.3 $/GJ. Popp et al (2011a) report bioenergy supply prices of up to 7 $/GJ for producing about 300 EJ of bioenergy.

Geological storage capacity

Another critical need for bioenergy with CCS is available and safe geological carbon storage (Azar et al., 2010; Kriegler et al., 2013). The uncertainty of available geological storage capacity is huge. Estimates range between 100 and 200,000 GtCO_2 globally (Bradshaw et al., 2007). Currently, about 1 MtCO_2 is stored annually in the Sleipner field in the North Sea (Azar et al., 2010). To realize the levels of bioenergy use with CCS that are projected by IAMs for low GHG stabilization targets (see below), "… global storage activities must be some ten thousand times larger than at present. It cannot be taken for granted that there are sufficient and safe geological storage options, and sufficient political acceptability, for this technology to work at a large scale." (Azar et al., 2010, p. 200)

Bioenergy deployment in climate change mitigation scenarios

The mitigation potential of bioenergy with CCS is estimated at 2-10 GtCO_2/yr until 2050 – at carbon prices of 70-250 $/t$CO_2$ (McLaren, 2012; Smith et al., 2014). In IAMs, carbon prices reflect the marginal costs of climate change mitigation, i.e. the costs for the reduction of one additional unit of CO_2 emissions (Kriegler et al., 2014b). For climate protection scenarios that stabilize the atmospheric GHG concentration at 450 ppm CO_2eq in 2100, several IAMs project strongly increasing carbon prices throughout the 21st century, reaching levels of more than 1000 $/t$CO_2$ in 2100 (Rose et al., 2014). Such high carbon prices incentivize the large-scale deployment of bioenergy with CCS, which provides negative CO_2 emissions besides low-carbon energy (Rose et al., 2014). IAMs with explicit representation of land-use dynamics and associated GHG emissions project global bioenergy deployment levels of 129-228 EJ/yr in 2050 and 255–324 EJ/yr in 2100 (Popp et al., 2014). The large-scale production of biomass is projected to require substantial amounts of land: bioenergy cropland increases by about 400-500 Mha throughout the 21st century and accounts for 24-36% of total cropland in 2100 (Popp et al., 2014), compared to 3% currently (Foley et al., 2011).

1.4.3 Afforestation and avoidance of deforestation

Biological carbon sequestration and storage

According to FAO (2010), the world's forests store huge amounts of carbon: 650 GtC globally. To put this into perspective, the annual emissions from deforestation between 1990 and 2010 were 0.5 GtC. A stop of deforestation and sustainable forest management can conserve existing forest carbon stocks. Moreover, afforestation can increase forest carbon stocks since trees take up more CO_2 through photosynthesis than they respire and thereupon store the absorbed carbon in vegetation and soil (FAO, 2010; Mackey et al., 2013; Smith et al., 2014). Due to this biological carbon sequestration and storage, afforestation can provide negative CO_2 emissions or rather CDR from the atmosphere (Smith et al., 2014; Tavoni & Socolow, 2013). Besides bioenergy with CCS, large-scale afforestation is among the most discussed CDR options in the current literature (Edenhofer et al., 2014a; Tavoni & Socolow, 2013). The fundamental difference between these two options it that one unit of land can be used several times for bioenergy production, while it can be used just once for afforestation – at least if climate change mitigation is the main goal of afforestation. Forest growth rates decrease with forest age (Smith et al., 2014), i.e. the rate of carbon sequestration or negative CO_2 emissions of one unit of afforested land decreases over time. However, even if forest growth saturates, the forest has to be maintained as forest permanently in the future to preserve the forest carbon sink, i.e. to prevent the emission of sequestered carbon back to the atmosphere. Disturbances such as fires, insect or disease outbreak, or future land-use change could release sequestered carbon back to the atmosphere (Ciais et al., 2013; Smith et al., 2014). Therefore, the two most limiting factors for large-scale afforestation as climate change mitigation strategy are available land and non-permanence/reversibility.

Climate change

Climate change has not only impacts on crop yields, but also on carbon stocks in the terrestrial biosphere (Field et al., 2014). As for agricultural crops, changes in temperature, precipitation and CO_2 concentration can influence photosynthesis and respiration of plants in the terrestrial biosphere (Houghton, 2013). For instance, climate change could alter carbon stocks in forests. According to biophysical process models, climate change increases global vegetation carbon stocks in the course of the 21st century – at least up to 4°C additional global warming (Friend et al., 2014). At higher levels of global warming the increase in global vegetation carbon stocks may stall or reverse.

More general, climate change has impacts on the carbon storage capacity of land, which reflects the potential of a unit of land to sequester and store carbon in vegetation and soil (Keith et al., 2009; Mackey et al., 2013). The carbon storage capacity is crucial for afforestation projects since it determines the mitigation potential of afforestation projects. Hence, climate change could alter the expectations of afforestation projects. Furthermore, the impacts of climate change on terrestrial carbon stocks are heterogeneous across the globe (Friend et al., 2014). Thus, the spatial suitability of land for afforestation might be affected by climate change.

Albedo

Changes in forest cover have impacts on the albedo, i.e. the reflectivity of the land surface. The albedo can range from 0 (black surface ~ low reflectivity) to 1 (white surface ~ high reflectivity) (Ciais et al., 2013). Modeling studies show that afforestation in seasonally snow-covered areas in high latitude regions reduces land surface albedo (forests are darker than snow), which could result in a warming effect since a darker land surface traps more heat (Bala et al., 2007; Jackson et al., 2008; Jones et al., 2013; Schaeffer et al., 2006). Such biophysical warming effects due to albedo changes could jeopardize biogeochemical cooling effects of CDR from large-scale afforestation (Ciais et al., 2013). Therefore, afforestation in high latitude regions could be counterproductive from a climate change mitigation perspective. In low latitudes (tropics), it is likely that afforestation results in a net (biophysical + biogeochemical) cooling effect (Ciais et al., 2013).

Mitigation potential and costs

Pricing CO_2 emissions from deforestation provides an economic incentive to reduce deforestation (Kindermann et al., 2008). Avoidance of deforestation is among the most cost-efficient land-based mitigation options (Edenhofer et al., 2014a). A 50% reduction in deforestation rates until 2030 is estimated to lower emissions from deforestation by 1.5-2.7 GtCO2/yr – at costs of 10-21 $/tCO_2$ (Kindermann et al., 2008). For afforestation, McLaren (2012) reports carbon sequestration rates of 1.5-3 $GtCO_2$/yr at carbon prices of 20-100 $/tCO_2$. The extension of land carbon pricing towards negative emissions is projected to rapidly increase forest cover through large-scale afforestation starting from carbon prices of 16 $/tCO_2$, associated with maximum carbon removal rates of 15 $GtCO_2$/yr, which decline over the century due to forest saturation and limits on available land for afforestation (Calvin et al., 2014; Edmonds et al., 2013; Tavoni & Socolow, 2013).

1.4.4 Competition for land

"Competition for land, in itself, is not a driver affecting food and farming in the future, but is an emergent property of other drivers and pressures. Modelling studies suggest that future policy decisions in the agriculture, forestry, energy and conservation sectors could have profound effects, with different demands for land to supply multiple ecosystem services usually intensifying competition for land in the future."
(Smith et al., 2010, p. 2941)

Global food demand is projected to increase in the coming decades due to population growth and increasing shares of livestock products in human diets (see section 1.4.1). At the same time, for ambitious climate targets, such as the 2°C target, strong reductions in GHG emissions are required in all sectors of the economy at the global scale (see section 1.2). In the AFOLU sector, forest protection for climate change mitigation would reduce the available land for agricultural expansion (Smith et al., 2010). Hence, avoidance of deforestation might increase competition for land in the AFOLU sector. Moreover, many low stabilization scenarios rely on land demanding CDR options, such as bioenergy with CCS or afforestation, which could further increase competition for land (see sections 1.2, 1.4.2 and 1.4.3). Competition for land has potential positive or negative effects on biosphere, economy and society (Smith et al., 2014). In classical economic theory, "competition is seen as a key element of technological progress and economic efficiency" (Haberl, 2014, p. 2). For instance, future competition for land due to large-scale bioenergy deployment may trigger investments in agricultural R&D targeted at yield increases, in particular if forest is protected at the same time (Popp et al., 2011a). Such land-use intensification, however, was associated with additional GHG emissions in the recent past (see section 1.3.4). On the other hand, if forest is not protected, large-scale bioenergy deployment may increase agricultural expansion into forests, associated with the loss of ecosystem services, such as biodiversity, carbon storage and water purification (Popp et al., 2011a). In general, the outcome of competition for land in a free market is socially not optimal if prices do not properly reflect external costs (Haberl, 2014; Rohlf, 2010), such as additional GHG emissions from land-use intensification and agricultural expansion into forests.

2 Thesis objective and research questions

The main objective of this thesis is to investigate the potential contribution of the global land system to climate change mitigation in the 21st century.

As highlighted in the background section, global food demand is projected to increase in the coming decades due to a growing and more affluent world population. In addition to agriculture, ambitious climate targets could further increase the pressure on the global land system in the 21st century. Currently, bioenergy use in combination with CCS, afforestation and avoidance of deforestation are the most discussed land-based mitigation options (see sections 1.2 and 1.4). To evaluate these land-based options, it is crucial to investigate their mitigation potential and land requirement under consideration of interactions with the traditional agricultural sector. For instance, land-based mitigation might compete for land with food crop production. Such competition for land could result in land-use intensification, which in turn might cause additional GHG emissions that jeopardize the intended mitigation effect of the original measure. Thus, the overarching and guiding research question of this thesis is:

What is the global potential of land-based carbon mitigation in the 21st century, what are the associated land requirements and what are the implications for the agricultural sector?

In order to answer this overarching research question, it is subdivided into five specific research questions, which are addressed in the main part of this thesis in chapters II-VI. Each research question is followed by a brief motivation.

Chapter II What is the carbon mitigation potential of global forest and land-use protection schemes?

Recent climate talks in Warsaw (COP-19) have made progress towards adopting the United Nations Reducing Emissions from Deforestation and Forest Degradation (REDD) mechanism (UNFCCC, 2013). Therefore, REDD is high on the political as well as on the scientific agenda. REDD aims to provide economic incentives for carbon stock conservation through avoidance of deforestation. If such a forest protection scheme is not implemented globally, the expansion of agriculture into forests might be displaced to non-participating countries, which is known as international leakage (Ebeling & Yasue, 2008; Gan & McCarl, 2007; Lambin & Meyfroidt, 2011). However, if forest protection is implemented globally, agricultural expansion could be displaced into carbon rich non-forest ecosystems, causing additional CO_2 emissions that would not have occurred without a global forest protection scheme. Therefore, the question of the net mitigation potential of a global forest protection scheme arises. Moreover, it is of interest if such externalities could be avoided by more comprehensive global land-use protection schemes that go beyond forest protection.

Chapter III How much bioenergy can be supplied at what price, with and w/o GHG emissions pricing in the land system?

Due to its flexibility, bioenergy is expected to play an important role in the future energy mix (see section 1.4.2). The substitution of fossil fuels with modern biomass provides low-carbon energy. If bioenergy is combined with CCS, it could provide energy and remove carbon from the atmosphere at the same time. However, the mitigation potential of bioenergy with CCS largely depends on biomass supply, which is strongly interlinked with the land system. Bioenergy production likely competes with food production for fertile land, which should be reflected in bioenergy supply prices. As land is a limited resource, the question arises how bioenergy prices scale with the level of bioenergy deployment. In addition, large-scale bioenergy production likely causes additional GHG emissions from deforestation and increased fertilizer use, which counteracts the mitigation effect of bioenergy use. Pricing GHG emissions from land-use and land-use change could potentially control such adverse side effects, but might also increase bioenergy supply prices.

Chapter IV How does irrigation in bioenergy production affect land and water resources, and what are the impacts on bioenergy prices?

IAMs project global bioenergy deployment levels of 255–324 EJ/yr in 2100 for a 450 ppm CO_2eq stabilization target in 2100 (see section 1.4.2). In these scenarios, bioenergy is largely combined with CCS to generate negative CO_2 emissions besides secondary energy. Bioenergy crops can be produced without (rain-fed) and with irrigation. Rain-fed bioenergy production relies only on green water resources (run-off infiltrated into the soil). Contrary, irrigation of bioenergy crops requires blue water (rivers, lakes or aquifers) in addition to green water resources. Irrigation can increase bioenergy crop yields considerable (Beringer et al., 2011). Therefore, irrigation could reduce the land requirements for bioenergy production and thereby lower the pressure in the land system, which should be reflected in bioenergy prices. However, irrigation of bioenergy crops likely increases the pressure on blue water resources. Today, agriculture accounts already for about 70% of total global blue water withdrawals (see section 1.3.4). Severe water scarcity is reported for about 50% of total global river basins (see also section 1.3.4). Therefore, the question arises how the prohibition of irrigated bioenergy production would affect bioenergy cropland requirements and bioenergy prices.

Chapter V How much land do afforestation and bioenergy with CCS require for how much CDR?

CDR is projected to play a key role for ambitious climate targets in terms of feasibility and mitigation costs (see section 1.2). Currently, two land-based CDR options are highly debated: afforestation and bioenergy with CCS. The major difference between afforestation and bioenergy with CCS is that one unit of land can be used just once for afforestation but several times for bioenergy production (see sections 1.4.2 and 1.4.3). Afforestation and bioenergy production likely compete for land with each other and with agricultural food production. Therefore, several questions arise: What incentives (reward for CDR through carbon prices) are required for the economic feasibility of afforestation and bioenergy with CCS? How much land does each of the two options require for how much CDR throughout the 21st century? Do afforestation and bioenergy with CCS interfere with each other due to competition for land?

Do additional N_2O emissions from increased fertilizer use jeopardize CDR of land-based mitigation options?

Chapter VI What are the direct and indirect effects of moderate climate change on terrestrial carbon stocks and what are the implications for land-based carbon mitigation?

For 2011, the atmospheric GHG concentration is estimated to be 430 ppm CO_2eq (see section 1.1). Limiting the increase in global mean temperature to below 2°C requires a stabilization of the atmospheric GHG concentration at 450 ppm CO_2eq in 2100 (see section 1.2). Therefore, even if ambitious climate polices are successful, current climatic conditions are subject to moderate change in the course of the 21st century. Climate change (temperature, precipitation and CO_2 concentration) has impacts on agricultural yields (see section 1.4.1), which might alter cropland requirements and thus deforestation rates. Accordingly, forest carbon stocks could be affected indirectly by climate change through land management. In addition, climate change has direct impacts on the carbon storage capacity of land, which might affect existing forest carbon stocks as well as the expectations of afforestation projects (see section 1.4.3). Thus, several question arise: What are the direct and indirect effects of moderate climate change on terrestrial carbon stocks? What is the ratio of direct and indirect effects? Does moderate climate change affect the mitigation potential of a land-based climate policy that provides incentives for afforestation and avoidance of deforestation?

3 Research approach

As pointed out above, the main objective of this thesis is to investigate the potential contribution of the global land system to climate change mitigation in the 21st century. This section motivates the use of a spatially explicit economic land-use model for this purpose and provides a description of key model characteristics.

3.1 The need for spatially explicit economic land-use modeling

Land-use allocation is an economic problem

Besides human and manufactured resources, the natural resource land is needed for the production of any physical good (Myers, 2012). In particular agriculture and forestry rely on land as production factor (Verburg et al., 2013). The natural resource land has two key characteristics. First, due to its natural existence, the economic value or rent of land is not a property of land itself, but depends solely on the use of land for producing goods (Myers, 2012) and the provision of ecosystem services (Kooten, 2011). Second, land is a limited resource because the land surface of the earth is finite. This biophysical limit of the resource land could lead to competition for land (see section 1.4.4). In short, the allocation of land to different uses is clearly an economic problem.

Spatially explicit information matters for land-use allocation

Climate, geography and soil properties affect the suitability of land for agriculture (Ramankutty et al., 2002). For instance, temperate and tropical climate zones are much more suitable for agriculture than deserts. Mountains might have a favourable climate for agriculture but are often not accessible with machinery. Hence, spatially explicit properties of plant growth affect the process of land-use allocation. Overall, climate and soil properties shape the terrestrial biosphere of the earth. For instance, tropical forests store on average about 50% more carbon per unit area than boreal forests (Kooten, 2011). Thus, agricultural expansion into forests causes substantially higher CO_2 emissions in tropical than in boreal regions (FAO, 2010). Likewise, carbon sequestration due to growth/regrowth of natural vegetation depends on climate zones and soil properties. For instance, the carbon sequestration rate of tropical forests is on average twice that of boreal forests (Kooten, 2011). In short, spatially explicit properties of the terrestrial biosphere are of paramount importance for investigating a) the impacts of agriculture on land-use change emissions and b) the mitigation potential of afforestation and avoidance of deforestation.

Pricing CO_2 emissions from the land system alters the opportunity costs of land

A price on CO_2 emissions from land-use change reflects the value of carbon storage in the terrestrial biosphere for climate change mitigation. Hence, including CO_2 emissions from land-use change in a carbon pricing mechanism will affect the opportunity costs of land-use, i.e. the foregone value of alternative uses when land is used for a particular activity (Kooten, 2011). For instance, pricing CO_2 emissions could render deforestation for agricultural expansion unattractive. As a result, forests and their carbon stocks would be conserved. Extending the carbon price towards negative CO_2 emissions rewards CDR from the atmosphere. Land-based carbon mitigation options, such as afforestation or bioenergy with CCS remove carbon from the atmosphere through photosynthesis and store it biologically or geologically (see sections 1.4.2 and 1.4.3). Hence, rewarding CDR from the atmosphere besides pricing CO_2 emissions will further affect the opportunity costs of land-use. For instance, using fertile land for afforestation or bioenergy production could become economically more attractive than food crop production. Thus, pricing CO_2 emission from the land system would add another dimension to the land-use allocation process besides agriculture, forestry and human settlements.

Why modeling?

"All of our understanding of the world is in the form of models: from simple mental models to computer models. […] Models and simulations have always been an essential part of the human experience: Before arriving at a decision, we use mental models to determine possible outcomes, and evaluate their potential costs and benefits. […] In formalized systems analysis and simulation, mental models are translated into computer models, and the simulations of alterative outcomes under different conditions are made on the computer. The main advantage is that the computer can track the multitude of implications of complex relationships and their dynamic consequences much more reliably than the human mind." (Bossel, 2007, p. 3)

3.2 The MAgPIE model

"Model-based simulations of the future need to be undertaken over time periods that incorporate the short-term for policy design and implementation as well as the mid- and long-term effects on the land system of global change drivers such as climate, social, economic and technological change. Some aspects of land system change can only be evaluated over longer time horizons, e.g. the impacts of climate change and climate-related policies and investments,

but also ecological processes such as the regeneration of forests. To account for possible differential impacts on longer time scales, model-based assessments would also have to estimate long-term effects (approximately to the year 2100)."
(Rounsevell et al., 2012, p. 905)

General model description

Central to this thesis is the Model of Agricultural Production and its Impacts on the Environment (MAgPIE), which is developed and managed at the Potsdam Institute for Climate Impact Research (PIK) in joint cooperation of the research domains II (Climate Impacts and Vulnerabilities) and III (Sustainable Solutions) (Dietrich et al., 2014; Lotze-Campen et al., 2008; Lotze-Campen et al., 2010; Popp et al., 2010; Popp et al., 2011a; Popp et al., 2011b; Popp et al., 2014; Schmitz et al., 2012). The MAgPIE model has been used for all studies presented in the main part of this thesis in chapters II-VI. The following gives an overview of the MAgPIE model. More details and the description of model features specific to research questions can be found in the methods sections of chapters II-VI. Table 1 (at the end of chapter I) provides a summary of model settings used in chapters II-VI.

MAgPIE is a global multi-regional economic land-use optimization model for simulations up to the year 2100. It is a partial equilibrium model of the agricultural sector that links socio-economic inputs for ten world regions with high-resolution biophysical inputs. MAgPIE optimizes land-use patterns with the objective of minimizing global agricultural production costs and calculates the associated GHG emissions. Furthermore, MAgPIE derives economic indicators, e.g. bioenergy prices. The model simulations are subject to a number of assumptions, such as food demand (calculated based on population and income projections), land-use change regulation and trade liberalization. The socio-economic assumptions in MAgPIE are based on the Shared Socio-economic Pathways (SSP) concept, which is a new scenario framework for climate change research (O'Neill et al., 2014). This thesis focuses on SSP2, a pathway with intermediate challenges for adaption and mitigation. In general, SSP2 is characterized by the continuation of current trends in demographics, economic development, environmental protection and technological development. Food production is associated with costs for labor, capital, agricultural expansion, land-use intensification and transport of goods. The process of cost minimization happens in a recursive dynamic mode, with simulation time steps of 5-10 years length. Hence, simulation time steps in the MAgPIE model are solved iteratively as opposed to models with inter-temporal optimization (perfect foresight) that consider all simulation time steps at once. Recursive dynamic or myopic optimization mimics limited information availability for decision-making in the real world. The MAgPIE model solves the cost minimization problem by endogenous optimization of land expansion and contraction, investments in yield-increasing technological change and shifts in spatial production patterns.

Biophysical input to the MAgPIE model is provided by the Lund-Potsdam-Jena model for managed Land (LPJmL), which is also developed and maintained at PIK (Müller et al., 2007; Müller & Robertson, 2014). The biophysical process model LPJmL simulates spatially explicit (0.5 degree longitude/latitude) crop yields, carbon densities of natural vegetation and water availability under consideration of climate projections from Global Circulation Models (GCMs). This thesis focuses on climate projections for RCP2.6. Land types in MAgPIE (0.5 degree longitude/latitude) consist of cropland, pasture, forest, forestry, other land (e.g. non-forest natural vegetation, abandoned agricultural land, deserts) and urban areas (Erb et al., 2007; Krause et al., 2013). Due to computational constraints, spatially explicit inputs are clustered into simulation units before entering the model (Dietrich et al., 2013).

For each MAgPIE run, key output variables, such as agricultural area, yield-increasing technological change and land-use change emissions, are validated against observed data. In order to test the stability of model result, sensitivity analysis with crucial model inputs and parameters has been performed in each study presented in chapters II-VI.

Calculation of GHG emissions

For each simulation time step, MAgPIE calculates the GHG emissions associated with the cost-optimized land-use pattern. CO_2 emissions due to land-use change are calculated for each simulation unit as the difference in carbon stocks between the previous and the current simulation time step. For instance, if forest is cleared for agricultural expansion, the carbon stocks (vegetation, litter and soil) of this simulation unit decrease according to the difference in carbon density between forest and cropland, resulting in CO_2 emissions. N_2O emissions from agriculture mainly depend on the efficiency of organic and inorganic fertilizer use, and animal waste management. CH_4 emissions originate from livestock management (enteric fermentation, animal waste) and paddy rice production.

For this thesis, the process of natural vegetation re-growth on abandoned agricultural has been implemented in MAgPIE (see methods part in chapter V for details). Regrowth of natural vegetation leads to biological carbon sequestration and storage, and hence CDR from the atmosphere (negative CO_2 emissions). The annual rate of biological carbon sequestration follows a S-shaped, age dependent, growth curve that starts with low but increasing growth rates, followed by decreasing growth rates later on until saturation.

Pricing of GHG emissions

GHG emissions in MAgPIE can be priced to provide economic incentives for GHG emission reductions. For that purpose, the costs entering the objective function of the model are extended by the costs for GHG emissions certificates. Thus, under GHG emissions pricing, MAgPIE minimizes agricultural production costs and associated GHG emissions at the same time. The mitigation of CO_2 emissions is implemented endogenously in the model. For instance, pricing CO_2 emissions from deforestation can render agricultural expansion into forests unattractive compared to yield-increasing technological change or international trade.

For this thesis, carbon pricing has been extended towards negative CO_2 emissions (see chapter V). Within the land system, negative CO_2 emissions can be generated through afforestation (see section 1.4.3). The costs in the objective function of the model are lowered by the amount of sequestered carbon times the carbon price. Therefore, rewarding negative CO_2 emissions provides incentives for afforestation, which is implemented as managed re-growth of natural vegetation. In high latitude regions, changes in albedo due to large-scale afforestation could jeopardize the cooling effect of CDR from afforestation (see section 1.4.3). Therefore, high latitude regions above 50 degree North and South can be excluded in MAgPIE from the available area for afforestation (see chapter VI).

Land-based climate polices

Land-based climate polices in MAgPIE are represented by a price on GHG emissions and/or 2nd generation bioenergy demand. Furthermore, for each climate policy the land pools subject to carbon pricing need to be specified. For instance, the carbon price can be applied only to emissions from deforestation or to all land-use change emissions. GHG prices and bioenergy demand are exogenous to the MAgPIE model and are derived from the Regional Model of Investments and Development (REMIND), which is likewise developed and maintained at PIK (Luderer et al., 2013). REMIND is a global multi-regional model for the assessment of climate change mitigation polices throughout the 21st century that integrates interactions of the energy system, the economy and the climate system. This thesis uses GHG price and bioenergy demand trajectories from REMIND that have been derived for ambitious climate targets, such as GHG stabilization at 450 ppm CO_2eq in 2100.

4 Structure of the thesis and overview

The main part of this thesis consists of five research articles in chapters II-VI that address the research questions formulated in section 2 of this introduction (chapter I). The articles are published in peer-reviewed journals (chapters II-V) or are submitted (chapter VI). The author's contributions to these research articles are stated at the end of this thesis (statement of contributions). The articles form self-contained chapters that have their own layout and references but are interlinked with each other by contributing to the main objective of this thesis and by using a common research approach (MAgPIE model; see section 3). Chapter VII provides a summary of results, presents key findings, discusses model limitations and gives an outlook on further research. The bibliography at the end of this thesis contains the references from chapters I and VII.

The following gives an overview of the content of chapters II-VI. Table 1 provides a summary of key scenario settings in the MAgPIE model and key output variables.

Chapter II analyzes the contribution of global land-use protection schemes to climate change mitigation throughout the 21st century. Besides a reference scenario, two global land-use protection scenarios stand in the center of chapter II: forest protection and comprehensive land-use protection. Forest protection / comprehensive land-use protection are incentivized by pricing CO_2 emissions from deforestation / all land-use changes. To identify the mitigation potential of global land-use protection schemes, the scenario analysis focuses on land-use change and associated carbon stock dynamics. Carbon stock dynamics are differentiated into emissions from land-use change, carbon uptake from regrowth of natural vegetation, and climate change impacts based on RCP2.6 climate projections (see section 1.2). Sensitivity analysis is performed for biophysical inputs (climate impacts), the demand side (food demand) and the supply side (costs for yield-increasing technological change).

Chapter III presents bioenergy supply curves with and w/o GHG emissions pricing in the land system. The supply curves are constructed by deriving bioenergy supply prices (marginal costs of production) for various bioenergy demand scenarios with the spatially explicit land-use allocation model MAgPIE. Pricing land-related GHG emissions is geared to reduce the environmental externalities of bioenergy production, such as CO_2 emissions from deforestation or N_2O emissions from fertilizer use. The MAgPIE model treats the trade-off between agricultural expansion and investments in yield-increasing technological change endogenously. Thus, the economic impacts of pricing land-related GHG emissions are reflected in bioenergy prices. The analysis presents the impacts of GHG emissions pricing on global and regional bioenergy supply prices, land-use patterns and CO_2 emissions.

Chapter IV investigates the trade-offs between land and water requirements for large-scale bioenergy production compatible with a 450 ppm CO_2eq stabilization target in 2095. Two scenarios stand in the center of chapter IV: fulfillment of an exogenous global bioenergy demand path (300 EJ in 2095) with and w/o irrigation of bioenergy crops. The scenario analysis focuses on the regional allocation of bioenergy production, land-use dynamics, water withdrawals and bioenergy prices. To test the stability of model results, sensitivity analysis with different assumptions on water productivity is performed.

Chapter V investigates the global CDR potential of large-scale afforestation and bioenergy use with CCS for the 21st century. Besides a business-as-usual scenario (no land-based mitigation), three mitigation scenarios are in the center of Chapter V: afforestation, bioenergy with CCS and the combination of both. In the mitigation scenarios, all land-related GHG emissions are priced, which provides incentives to reduce deforestation and lower fertilizer use for bioenergy production. The extension of carbon pricing towards negative emissions provides incentives for land-based CDR. For all scenarios the cost-efficient deployment of afforestation and bioenergy with CCS is derived endogenously in the MAgPIE simulations. The scenario analysis presents land requirements and associated CDR of afforestation and bioenergy with CCS throughout the 21st century. Sensitivity analysis is performed, among others, for GHG prices, CCS capacity and bioenergy yields.

Chapter VI addresses global scale interactions between the climate system, anthropogenic land-use and the terrestrial carbon balance in the context of moderate climate change (RCP2.6) and a land-based climate policy. Besides a reference scenario, three scenarios stand in the center of chapter VI. (1) A land-based climate policy that provides economic incentives for afforestation and avoidance of deforestation by pricing land-related CO_2 emissions. (2) RCP2.6 climate impacts on crop yields and carbon stocks in the terrestrial biosphere. (3) The combination of a land-based climate policy and RCP2.6 climate impacts. In the model simulations, afforestation is prohibited above 50 degree North and South since albedo effects likely jeopardize the cooling effect of CDR in high latitude regions (see sections 1.4.3 and 3.2). The scenario analysis focuses on global land-use and carbon stock dynamics throughout the 21st century, with carbon stock changes attributed to (a) direct impacts of climate change and (b) land management. Sensitivity analysis is performed for RCP2.6 climate projections.

Table 1: Summary of key scenario settings in the MAgPIE model and key output variables for chapters II-VI. Scenario names are *italic* (abbreviations in brackets), followed a brief description in the following line(s).

Ch.	MAgPIE scenario setup	Output variables
II	**Global land-use protection schemes** *Reference scenario (Ref)* No pricing of CO_2 emissions *Forest protection (REDD)* Pricing CO_2 emissions from deforestation *Comprehensive land-use protection (All)* Pricing CO_2 emissions from all land-use changes	Global land-use and carbon stock dynamics throughout the 21st century and agricultural yield increases
III	**Bioenergy supply curves** 73 bioenergy demand scenarios with and w/o GHG emissions pricing (CO_2 emissions from deforestation, N_2O/CH_4 emissions from agricultural land-use). The price response of MAgPIE to these scenarios is used to construct the bioenergy supply curves.	Global and regional bioenergy supply prices, land requirements for bioenergy production, deforestation and CO_2 emissions
IV	**Production of 300 EJ bioenergy in 2095** *Reference scenario (BE)* Rainfed and irrigated bioenergy crop production *Rainfed only (BE_RF)* Only rainfed bioenergy crop production	Regional and global land-use dynamics, water withdrawals and bioenergy prices
V	**Land-based CDR** *Business-as-usual (BAU)* No pricing of GHG emissions *Afforestation (AFF)* Price on land-related GHG emissions and reward for CDR from afforestation *Bioenergy with CCS (BECCS)* GHG prices and reward for CDR from BECCS *Combined setting (AFF+BECCS)* Combination of AFF and BECCS	Global scale land requirements and associated CDR (negative CO_2 emissions) of afforestation, bioenergy with CCS and the combination of both throughout the 21st century
VI	**Impacts of climate change on land-based mitigation** All scenarios include modern bioenergy demand consistent with GHG stabilization at 450 ppm CO_2eq in 2100 / RCP2.6 *Reference scenario* No carbon prices No climate impacts (static climatic conditions) *Land-based climate policy (LCP)* Price on land-related GHG emissions and reward for CDR from afforestation (excluding high latitudes) *Climate impacts (RCP2.6)* Climate impacts on crop yields and natural vegetation carbon stocks *Combined setting* Land-based climate policy with RCP2.6 climate impacts	Global scale land-use and carbon stock dynamics throughout the 21st century and agricultural yield increases

II Land use protection for climate change mitigation[*]

Authors:
Alexander Popp, Florian Humpenöder, Isabelle Weindl, Benjamin Leon Bodirsky, Markus Bonsch, Hermann Lotze-Campen, Christoph Müller, Anne Biewald, Susanne Rolinski, Miodrag Stevanovic and Jan Philipp Dietrich

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Land-use protection for climate change mitigation

Alexander Popp[1]*, Florian Humpenöder[1], Isabelle Weindl[1], Benjamin Leon Bodirsky[1,2], Markus Bonsch[1], Hermann Lotze-Campen[1], Christoph Müller[1], Anne Biewald[1], Susanne Rolinski[1], Miodrag Stevanovic[1] and Jan Philipp Dietrich[1]

Land-use change, mainly the conversion of tropical forests to agricultural land, is a massive source of carbon emissions and contributes substantially to global warming[1-3]. Therefore, mechanisms that aim to reduce carbon emissions from deforestation are widely discussed. A central challenge is the avoidance of international carbon leakage if forest conservation is not implemented globally[4]. Here, we show that forest conservation schemes, even if implemented globally, could lead to another type of carbon leakage by driving cropland expansion in non-forested areas that are not subject to forest conservation schemes (non-forest leakage). These areas have a smaller, but still considerable potential to store carbon[5,6]. We show that a global forest policy could reduce carbon emissions by 77 Gt CO_2, but would still allow for decreases in carbon stocks of non-forest land by 96 Gt CO_2 until 2100 due to non-forest leakage effects. Furthermore, abandonment of agricultural land and associated carbon uptake through vegetation regrowth is hampered. Effective mitigation measures thus require financing structures and conservation investments that cover the full range of carbon-rich ecosystems. However, our analysis indicates that greater agricultural productivity increases would be needed to compensate for such restrictions on agricultural expansion.

Driven mainly by the fertilizing effects of increased levels of CO_2 in the atmosphere, the land system has been a terrestrial sink for carbon in recent decades[2]. However, the role of land for sequestering carbon is counteracted, as the carbon emissions from land-use and land-cover change accounted for approximately 12% of all anthropogenic carbon emissions from 1990 to 2010[3]. The future development of forest area is uncertain, but deforestation is projected to persist as a significant emission source in the absence of new forest conservation policies, especially under increasing demand for agricultural commodities. Compared to climate change mitigation options in the energy and transport sector, recent research has indicated low opportunity costs and significant near-term mitigation potential through reducing deforestation, promoting avoided deforestation in tropical countries as a cost-effective mitigation option[7].

Despite the general scientific agreement on environmental benefits of forest conservation, and although the United Nations Framework Convention on Climate Change (UNFCCC) has affirmed the potential role of forests in stabilizing the global climate, no global action has yet emerged to conserve natural forests. Several issues have so far prevented the development of conservation mechanisms supported under the UNFCCC (ref. 8). In particular, the design of financing mechanisms[4], but also environmental and socio-political concerns associated with REDD (Reduced Emissions from Deforestation and Degradation) and its variations are being intensively discussed[9,10]. One key issue for the implementation of REDD is how to address leakage of emissions[11]. Without full participation of all countries in a forest conservation scheme, emission reductions in one location could result in increased emissions elsewhere, as agricultural expansion, the main driver for deforestation, could just be displaced rather than avoided[12].

However, carbon leakage is not only relevant in the context of regionalized forest protection efforts. Another risk associated with a global REDD scheme that so far has not been quantified in the literature is the shift of land-use pressures to non-forest ecosystems (non-forest leakage) simply because they are the only remaining resource for agricultural expansion[13]. Such ecosystems may also be rich in carbon. First, areas under natural vegetation other than forests, such as shrublands and savannas, can also store considerable amounts of aboveground carbon, especially in Africa, but also in Latin America and Asia[6]. Second, carbon-rich soils also play a major part in the terrestrial carbon balance and have to be taken into consideration[5,14]. Grasslands and pastures, unlike cropland, maintain a permanent vegetation cover and, therefore, have a high root turnover, leading to substantial soil organic carbon storage[15]. For this reason, carbon stocks decline strongly after land is converted from grasslands and pastures to cropland[5]. Finally, agricultural activity can reduce carbon sequestration by preventing regrowth of natural vegetation on abandoned agricultural land[16].

In contrast to the current political discussion, which focuses only on REDD implementation, recent global modelling assessments have focused on the implementation of a global terrestrial carbon policy covering all regions and land types[17,18]. To avoid the negative consequences of a global forest conservation policy, a profound understanding of potential implementation failures, such as leakage into land types other than forests, is needed.

Here, we estimate land-use and associated carbon dynamics for different global terrestrial carbon policies at global and regional scale using the land-use optimization model MAgPIE (Model of Agricultural Production and its Impacts on the Environment—see Methods)[19]. Biophysical inputs for MAgPIE, such as agricultural yields, carbon densities and water availability, are derived from a dynamic global vegetation, hydrology and crop growth model, the Lund–Potsdam–Jena model for managed Land (LPJmL; refs 20,21). LPJmL provides the climate- and CO_2-driven changes in carbon densities, agricultural productivity and water availability of a 2 °C scenario (RCP2.6) to drive MAgPIE simulations. For this study, we assume ambitious mitigation policies with different contributions of the land-use sector in three scenarios: no terrestrial carbon policy in the reference scenario (Ref); a global terrestrial land-use policy that considers carbon emissions from deforestation

[1]Potsdam Institute for Climate Impact Research (PIK), Telegrafenberg, PO Box 60 12 03, D-14412 Potsdam, Germany. [2]Commonwealth Scientific and Industrial Research Organization, St Lucia, Queensland 4067, Australia. *e-mail: popp@pik-potsdam.de

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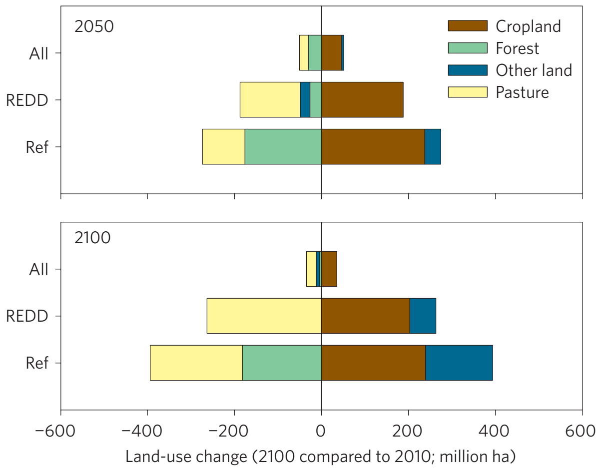

Figure 1 | Change in global land pools. The upper figure shows changes from 2010 to 2050 and the lower figure changes from 2010 to 2100 for the reference case (Ref) without land-use mitigation, a terrestrial land-use policy that considers carbon emissions from deforestation only (REDD) and a terrestrial carbon policy that accounts for emissions from all land types (All).

only in the REDD scenario; a global terrestrial carbon policy introduced by a universal carbon tax on greenhouse gas emissions from all terrestrial systems in the All scenario. To account for uncertainty in climate projections, we compute changes in carbon densities, agricultural productivity and water availability for the implementation of the RCP2.6 scenario in five different global circulation models (GCMs). We generally report mean values across all GCMs, while single GCM outputs and standard deviations can be found in Supplementary Table 1. In addition to the default scenarios with different GCM inputs, we perform sensitivity analyses with crucial exogenous parameters (demand for agricultural products, costs for agricultural yield increases and tax on terrestrial carbon emissions) to test the stability of our results in terms of cumulative carbon emissions (see sensitivity analysis in the Supplementary Information). It is important to note that the land-use model not only embraces the calculation of emissions from deforestation and other land-use change, but also the uptake of carbon from regrowth of secondary natural vegetation on abandoned agricultural land and carbon dynamics driven by climate change and CO_2 fertilization. In contrast to the mitigation of carbon emissions from land-use change, carbon uptake is not rewarded financially in our scenarios, as we focus in this study on protection policies. The MAgPIE model has been validated intensively for land-use, agricultural yield and land carbon dynamics and reproduces historical trends well (see also the validation section in the Supplementary Information). In addition, the ability of LPJmL to simulate global terrestrial carbon dynamics has been demonstrated in several previous studies[21,22].

Our reference scenario (Ref) without any terrestrial carbon policy is parameterized according to the 'SSP2' storyline of the shared socio-economic pathways[23] (see more detail in Methods). Our model results show that agricultural production increases are mainly realized by intensification on existing agricultural land (Supplementary Fig. 1) as well as by agricultural land expansion. In 2010, global cropland area was 1,454 million ha, pasture land area 3,079 million ha, global forest area 4,144 million ha and global other land area 4,229 million ha (see also Supplementary Fig. 2). At the global level, cropland increases by 237 million ha until the year 2050 and by 239 million ha until 2100, compared to 2010 (Fig. 1). Cropland area expands in developing and emerging regions, including countries of the Middle East and Africa (MAF), countries of Latin America and the Caribbean (LAM) and Asian countries, with the exception of the Middle East, Japan and Former Soviet Union states (ASIA), whereas it decreases in OECD90 countries (OECD; Supplementary Fig. 3). As a consequence, agricultural land is abandoned in the developed regions, as well as in LAM and MAF, where less pasture land is needed owing to more intensified livestock production systems that require less roughage for ruminant feed. Therefore, abandoned land increases by 154 million ha globally until 2100. According to this scenario, global land-use change emissions accumulate to 173 Gt CO_2 over the twenty-first century (Fig. 2a). Because of regrowth of secondary natural vegetation, 84 Gt CO_2 is sequestered on abandoned agricultural land up to 2100 (Fig. 2b).

Subsequently, we estimate the impacts of two different terrestrial land-use policies on land-use and carbon dynamics. Consistent with previous findings[17], a global terrestrial carbon policy (All scenario), introduced by a universal carbon tax on greenhouse gas emissions from all terrestrial systems, halts land-use change and associated carbon emissions, but decreases carbon uptake from regrowth on abandoned land (29 Gt CO_2 until 2100). However, if a terrestrial land-use policy considers carbon emissions from deforestation only (REDD scenario), forest loss is stopped whereas cropland expansion is reduced only marginally (cropland expansion of 203 million ha until 2100) compared to the Ref scenario (239 million ha) without any land-use policy. Such a policy restricts the areas available for cropland expansion, forcing agricultural expansion to switch to less suitable land. This also incentivizes intensification of existing croplands, leading to improved agricultural management and higher investments in yield-increasing technology (Supplementary Fig. 1). Under the REDD scenario, additional pasture land of 51 million ha is lost until 2100 compared to the Ref scenario, mainly in Africa and Latin America. At the same time, abandoned agricultural land area is reduced by 94 million ha compared to the Ref scenario. The reason is that less agricultural land is abandoned in Africa and Latin America if production cannot be extended into forested areas, and more land with non-forest natural vegetation is lost in Asia and Africa. Under the REDD scenario, carbon emissions from land-use change accumulate to 96 Gt CO_2, which is approximately 55% of the land-use-change-related emissions in the Ref scenario without any land-based mitigation. In addition, less agricultural land is taken out of production, thereby decreasing the uptake potential of secondary natural vegetation regrowth on abandoned land to 55 Gt CO_2.

Climate impacts such as precipitation and temperature changes and CO_2 fertilization based on RCP2.6 affect the carbon dynamics of the terrestrial system in all scenarios. Globally, carbon uptake due to climate change and CO_2 fertilization of 178 Gt CO_2, 176 Gt CO_2 and 180 Gt CO_2 can be attributed to the Ref, REDD and All scenarios, respectively, until 2100 (Fig. 2c). In all scenarios, highest carbon uptake driven by climate change and CO_2 fertilization can be observed until the mid-century as RCP2.6 peaks at 490 ppm CO_2 and then declines[24]. As a consequence of land-use change and carbon uptake, we conclude that the land system could contribute most to climate change mitigation if all ecosystems were to be included in a terrestrial land-use policy (All), taking up 191 Gt CO_2 until 2100 (Fig. 2d). In comparison, if only forest conservation measures are considered (REDD), the carbon uptake would be 55 Gt CO_2 lower compared to All, mainly owing to leakage effects into non-forest ecosystems and associated carbon emissions. Lowest net carbon uptake of 88 Gt CO_2 can be observed in the reference scenario without any land-use policy (Ref).

Our study shows that until 2050, without any land-use policy (Ref), land-use change would contribute about 13% to the global budget of 1,000 Gt CO_2 that must not be exceeded if global warming is to be limited to 2 °C with 66% likelihood[25], and about 7% if forest conservation measures are considered (REDD).

The results of our study emphasize that land-use policies should cover all land types to avoid non-forest leakage effects. Beyond the

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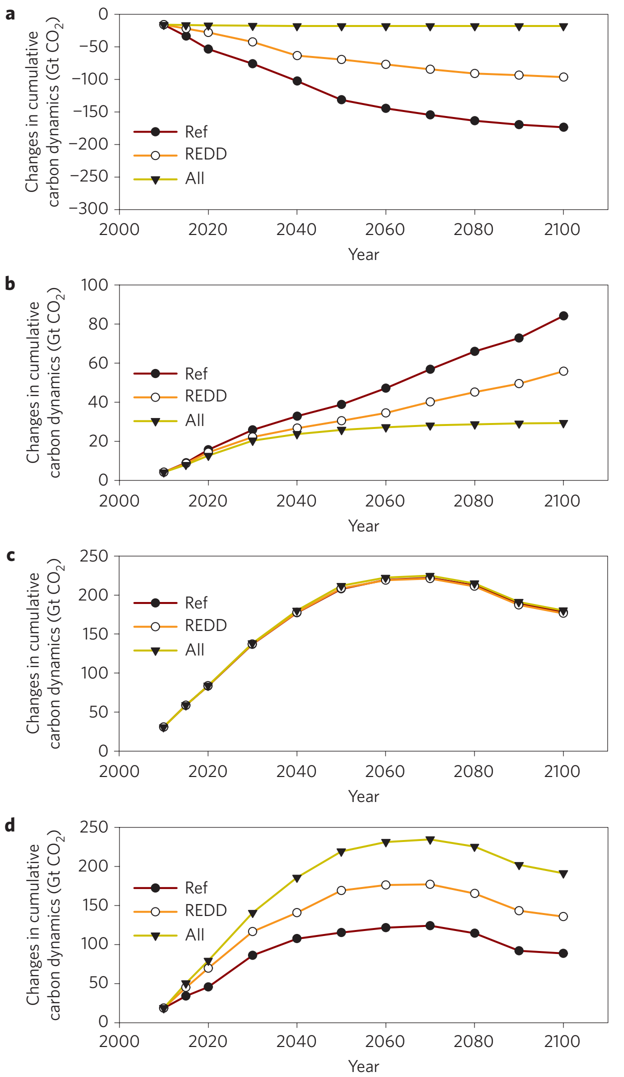

Figure 2 | Cumulative global carbon dynamics over the twenty-first century. a–d, Mean changes in carbon dynamics are calculated for all scenarios and across five GCMs for carbon losses due to land-use change (**a**), carbon uptake due to regrowth of secondary natural vegetation on abandoned agricultural land (**b**), carbon dynamics driven by climate change and CO_2 fertilization under RCP2.6 (**c**), and net carbon dynamics (**d**). Positive values represent terrestrial carbon sequestration, whereas negative values indicate loss of terrestrial carbon to the atmosphere.

importance of controlling land-use dynamics for climate change mitigation, which were analysed here, such policies should also account for other environmental assets, such as biodiversity. Land-use policies provide a huge opportunity to protect biodiversity as a co-benefit of maintaining forests[26]. But, as our analysis shows, forest protection policies such as REDD can lead to displacement of pressures, resulting from increasing demand for agricultural products, to less productive, non-forest ecosystems perceived to contain lower carbon levels. Those ecosystems, such as the tropical savannas of the Brazilian Cerrado, that nevertheless can support great levels of biodiversity or are home to endemic species of high conservational value can become increasingly threatened under such incomplete policies[13,27,28].

Implementing a global terrestrial carbon policy that includes all land types would have the largest benefits for both climate change mitigation and the protection of pristine landscapes. However, the implementation of such a scheme may be regarded as optimistic, given the slow progress in recent international negotiations. If a land-use policy that embraces all land types is considered politically impossible to implement, a simpler and more easily achievable approach to minimize the risks of any forest conservation scheme would be to identify and protect non-forest ecosystems of high value for carbon and biodiversity. So, if a forest conservation mechanism comes into operation, financing structures would have to be implemented which ensure that conservation investment is spread over the range of ecosystems not covered by REDD funding[13].

Our analysis indicates that higher agricultural productivity increases would be needed to compensate for reduced land availability for agricultural use (Supplementary Fig. 1). Generally, preserving ecosystems while enhancing agricultural production is a central challenge for sustainability[11]. Restrictions to agricultural expansion due to land conservation may affect land-use competition, with substantial effects on agricultural production costs and food prices[17,29,30]. And even if REDD is currently seen as a low-cost climate mitigation option, additional costs for the implementation and verification of REDD projects[7], as well as impacts on downstream economic values of current land uses, including employment and wealth generated by processing and service industries[9], could occur. These possible impacts need to be balanced against positive effects on CO_2 reductions. More efficient land management and major technological innovations in agriculture have the potential to prevent a global shortage of productive land[29], decrease carbon emissions from land-use change and enhance uptake of carbon from regrowth of secondary natural vegetation on abandoned agricultural land (see sensitivity analysis in the Supplementary Information). Large production increases are possible from, for example, closing yield gaps, but they will require considerable changes in nutrient and water management as well as shifting productivity frontiers to meet sustainability challenges[31]. On the other hand, demand-side measures such as changes in diet towards less products of animal origin can have 'land sparing' effects[32] which reduce the pressure from agricultural expansion on forests and other land (see Supplementary Fig. 4 and sensitivity analysis in the Supplementary Information). In contrast to such processes helping to reduce land-use pressure, enhanced competition in the land system could emerge due to financial rewards for the regrowth of natural vegetation (afforestation), mainly at the expense of pasture areas[33].

Methods

MAgPIE is a mathematical programming model projecting spatially explicit land-use dynamics in ten-year time steps until 2100 using recursive dynamic optimization[19]. The objective function of MAgPIE is the fulfilment of exogenously calculated food and livestock demand, defined for ten world regions (Supplementary Fig. 9 and Table 3), at minimum costs under socio-economic and biophysical constraints. Major cost types in MAgPIE are factor requirement costs (capital, labour, fertilizer and other inputs), land conversion costs, transportation costs to the closest market, investment costs for yield-increasing technological change and costs for carbon emission rights[29,34]. Whereas socio-economic constraints such as trade liberalization and forest protection are defined at the ten-region scale, biophysical constraints such as crop and pasture yields, carbon density and water availability, derived from the dynamic global vegetation model LPJmL (refs 20,21), as well as land availability, are introduced at the grid-cell level (0.5° longitude/latitude). The cost-minimization problem is solved through endogenous variation of spatial production patterns (intra-regionally and inter-regionally through international trade), land expansion and yield-increasing technological change (TC).

MAgPIE features land-use competition based on cost-effectiveness between food and livestock production and land-use-based mitigation such as avoided deforestation. Available land types are cropland, pasture, forest and other land (for example, non-forest natural vegetation, abandoned land, desert). Grid-cell-specific carbon densities for the different carbon stocks (vegetation, soil, litter) of the various land types are based on LPJmL simulations and IPCC guidelines for National Greenhouse Gas Inventories (IPCC 2006). MAgPIE

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calculates carbon emissions as the difference in carbon stocks (vegetation, litter and soil) between simulated time steps (more information in the Supplementary Information). Carbon uptake in MAgPIE occurs if regrowth of natural vegetation takes place on abandoned agricultural land (more information in the Supplementary Information). Mitigation of carbon emissions is stimulated by an exogenous tax on terrestrial carbon emissions. The carbon tax is multiplied by carbon emissions to calculate carbon emission costs, which enter the cost-minimizing objective function of MAgPIE. Therefore, stopping land-use change is an economic decision when emissions from land-use change are priced. In contrast, carbon uptake due to regrowth of natural vegetation is not rewarded financially in MAgPIE.

Our socio-economic assumptions are based on the Shared Socio-economic Pathways (SSPs) for climate change research[23]. In this study we choose SSP 2, a 'Middle of the Road' scenario with intermediate socio-economic challenges for adaptation and mitigation. Food, livestock and material demand is calculated using the methodology described in ref.35 and the SSP 2 population and gross domestic product projections ($\sim$65 EJ yr^{-1} in 2100, Supplementary Fig. 4). The SSPs do not incorporate climate mitigation policies by definition. Carbon tax ($\sim$US\$1,500 per tonne of CO_2 in 2100, Supplementary Fig. 5) in our study is aimed at ambitious climate change mitigation ($\sim$RCP 2.6 in 2100). The carbon tax has a level of US\$30 per tonne of CO_2 in 2020, starts in 2015 and increases nonlinearly at a rate of 5% per year. For consistency, MAgPIE simulations include temperature, precipitation and CO_2 trends and corresponding impacts on agricultural yields, water availability and carbon stocks in vegetation under a RCP2.6, derived by LPJmL. To account for uncertainty in climate projections for RCP 2.6, in this study we use climate data of the five GCMs: HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M.

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Author contributions

A.P. designed the overall study; F.H. and M.B. carried out the MAgPIE model runs. A.P. wrote the manuscript with important contributions from F.H., B.L.B., C.M. and M.B.; A.P., F.H., M.B. and B.L.B. analysed the results; F.H., I.W., B.L.B., M.B., J.P.D., A.P., M.S., A.B. and H.L-C. contributed in developing and improving the MAgPIE model; C.M. and S.R. provided biophysical input data from LPJmL; all authors discussed and commented on the manuscript.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to A.P.

Competing financial interests

The authors declare no competing financial interests.

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Land-use protection for climate change mitigation

Alexander POPP, Florian HUMPENÖDER, Isabelle WEINDL, Benjamin Leon BODIRSKY, Markus BONSCH, Hermann LOTZE-CAMPEN, Christoph MÜLLER, Anne BIEWALD, Susanne ROLINSKI, Miodrag STEVANOVIC, Jan Philipp DIETRICH

1. Additional results

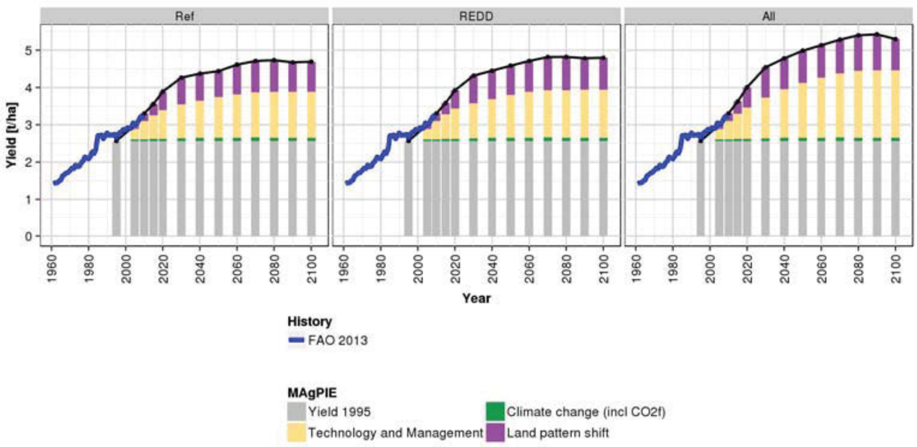

Figure SI-1: Global required agricultural yields [t/ha] aggregated across all crops for all 3 scenarios. The blue line shows historical data for agricultural yields (FAO 2013). The black line shows simulated global agricultural yields in MAgPIE. Grey bars represent agricultural yields in 1995. The colored bars indicate the contribution of different drivers to agricultural yield dynamics: climate change including CO_2 fertilization effects (green), improved agricultural management and technological change (yellow) and shifts in agricultural land use patterns due to e.g. increased agricultural trade or shifting cultivation mainly towards more high yielding feed crops to fulfill increasing demand for livestock products (purple).

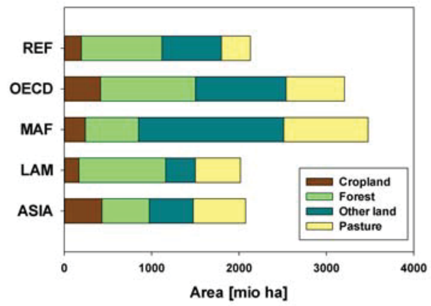

Figure SI-2: Regional land pools [mio ha] for the year 2100. Results are shown are for five aggregate regions: (1) OECD90 countries (OECD), (2) reforming economies of Eastern Europe and the Former Soviet Union (REF), (3) countries of the Middle East and Africa (MAF), (4) countries of Latin America and the Caribbean (LAM) and (5) Asian countries with the exception of the Middle East, Japan and Former Soviet Union states (ASIA. Brown bars represent cropland, yellow bars forest, green bars other land and blue bars pasture.

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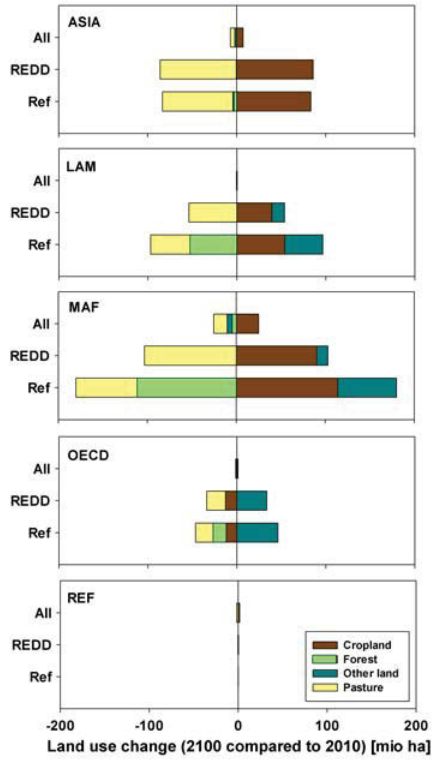

Figure SI-3: Change in regional land pools in million ha from 2010 to 2100 for the reference case (Ref) without land use mitigation, a terrestrial land use policy that considers carbon emissions from deforestation only (REDD) and a terrestrial carbon policy that accounts for emissions from all land types (All). Results are shown are for five aggregate regions: (1) OECD90 countries (OECD), (2) reforming economies of Eastern Europe and the Former Soviet Union (REF), (3) countries of the Middle East and Africa (MAF), (4) countries of Latin America and the Caribbean (LAM) and (5) Asian countries with the exception of the Middle East, Japan and Former Soviet Union states (ASIA).

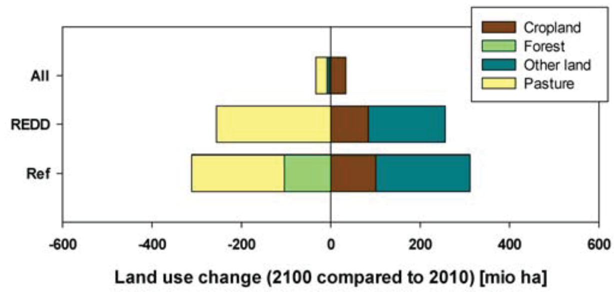

Figure SI-4 Change in global land pools in million ha from 2010 to 2100 for a demiterian scenario in which the consumption of livestock products in all countries is restricted to a maximum of 15% of caloric demand, which is equivalent to half of current consumption in Western countries (Bodirsky et al. 2014).

		Land use				Carbon dynamics			
		Cropland	Forest	Pasture	Other	Land total	LUC	Regrowth	CC & CO_2f
Ref	HadGEM2_ES	209,14	-192,91	-170,78	154,58	-14,85	-180,54	83,07	82,36
	IPSL_CM5A_LR	223,58	-125,17	-249,41	152,00	73,19	-145,05	85,40	133,21
	MIROC_ESM_CHEM	242,50	-160,69	-213,96	131,15	13,02	-159,10	68,54	103,22
	GFDL_ESM2M	252,76	-221,50	-190,62	158,37	180,05	-196,76	81,01	295,45
	NorESM1_M	268,01	-207,88	-235,48	174,35	191,61	-187,74	102,75	276,82
	Mean	***239,19***	***-181,63***	***-212,05***	***154,09***	***88,61***	***-173,15***	***84,17***	***178,25***
	SD	***23,30***	***38,83***	***32,06***	***15,49***	***94,37***	***21,18***	***12,24***	***100,36***
REDD	HadGEM2_ES	178,35	-0,09	-201,00	22,28	30,43	-100,81	52,14	78,55
	IPSL_CM5A_LR	187,84	-0,08	-294,69	107,05	100,27	-103,71	69,18	134,18
	MIROC_ESM_CHEM	227,93	-0,08	-303,42	76,49	44,86	-96,94	42,60	99,13
	GFDL_ESM2M	209,61	-0,18	-219,59	9,14	240,60	-105,53	51,96	294,57
	NorESM1_M	214,79	-0,05	-298,47	83,17	263,07	-76,47	63,33	276,54
	Mean	***203,70***	***-0,10***	***-263,43***	***59,63***	***135,84***	***-96,65***	***55,94***	***176,55***
	SD	***20,24***	***0,05***	***49,05***	***41,93***	***109,33***	***11,63***	***10,56***	***101,48***
All	HadGEM2_ES	27,19	-2,95	-14,00	10,76	89,91	-25,14	32,36	82,70
	IPSL_CM5A_LR	29,61	-5,27	-21,22	2,38	161,11	-14,99	38,20	137,44
	MIROC_ESM_CHEM	29,38	-7,28	-16,62	-5,84	105,16	-13,27	15,01	103,41
	GFDL_ESM2M	43,67	-2,81	-39,88	-1,02	300,86	-20,45	24,11	297,20
	NorESM1_M	44,45	-7,73	-20,46	-16,74	299,71	-18,01	37,40	280,32
	Mean	***34,86***	***-5,21***	***-22,44***	***-2,09***	***191,35***	***-18,73***	***29,42***	***180,31***
	SD	***8,46***	***2,32***	***10,18***	***10,17***	***102,92***	***4,68***	***9,81***	***101,31***

Table SI-1: Change in global land pools in million ha from 2010 to 2100 and cumulative carbon dynamics [Gt CO_2] until 2100 for all scenarios and considered GCMs, as well as the mean and standard deviation across all GCMs.

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2. Sensitivity analysis

In order to test the stability of our results in terms of cumulative carbon emissions, we perform sensitivity analyses with crucial exogenous parameters. Besides the sensitivity tests for several GCMs (see Table SI-1), we conducted a sensitivity analysis for (a) demand for livestock products, (b) costs for agricultural yield increases and (c) tax on terrestrial carbon emissions (see Table SI-2). We compare the mean value over GCM specific results for cumulative carbon emissions until 2100 of the sensitivity analyses (a, b and c) to the results of the SSP2 default case presented in the main paper (also mean value over GCM specific results).

a) Demand for livestock products (SSP2 food low)

To test the sensitivity of demand-side measures, such as changes in diets towards less products of animal origin, we included a demiterian scenario in which the consumption of livestock products in all countries is restricted to a maximum of 15% of caloric demand, which is approximately equivalent to half of current consumption in OECD countries (Bodirsky et al. 2014). Here, especially in the REF and REDD scenario, lower carbon emissions from deforestation and other land use change (LUC) and more uptake of carbon from regrowth of secondary natural vegetation on abandoned agricultural land (Regrowth) can be observed. In general, reductions in food demand lower the pressure on the land system but do not change the general findings of our study as highest net carbon uptake (Land total) can be observed in the ALL scenario.

b) Agricultural yield increases (SSP2 tc costs low, SSP2 tc costs high)

In order to increase total agricultural production, MAgPIE can endogenously decide to either invest in yield-increasing technology or increase cropland through land expansion (Popp et al. 2011, Dietrich et al. 2014). To test the stability of our results with respect to the trade-off between land expansion and yield-increasing technological change, we vary the parameters of the cost function for technological change from their default values to the low and the high end of their uncertainty range (see Dietrich et al. 2014). Lower costs for agricultural yield increases (*SSP2 tc costs low*) would lead to higher agricultural yields and lower therefore the pressure on the land system in all scenarios with less emissions from deforestation and other land use change (LUC) and more uptake of carbon from regrowth of secondary natural vegetation on abandoned agricultural land (Regrowth), especially in REF and REDD. All scenarios in *SSP2 tc costs low* show similar net carbon uptake (Land total). In turn, higher costs for land-use intensification (*SSP2 tc costs high*) increase, especially in REF and REDD, emissions from deforestation and other land use change (LUC). Therefore, net carbon uptake (Land total) is lower in all scenarios of *SSP2 tc costs high* compared to *SSP2 default*.

c) Tax on terrestrial carbon emissions (SSP2 C Price low)

In the *SSP2 default* scenarios, the carbon tax has a level of 30 \$/tCO_2 in 2020, starts in 2015 and increases by 5% yr^{-1}. For *SSP2 C Price low*, the level of the carbon tax is 5 \$/tCO_2 in 2020 respectively. The range for the sensitivity analysis is based on Kriegler et al (2013). Cumulative carbon emissions in REF, REDD and ALL are similar compared the *SSP2 default* case, which indicates that our findings are also valid at substantially lower carbon prices.

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		Land total	LUC	Regrowth	CC & CO_2f
Ref	*SSP2 default*	*-88,6*	*173,8*	*-84,2*	*-178,2*
	SSP2 food low	-157,9	115,1	-94,7	-178,3
	SSP2 tc costs low	-202,0	78,4	-100,8	-179,6
	SSP2 tc costs high	31,1	296,9	-87,9	-177,9
	SSP2 C Price low	-88,6	173,8	-84,2	-178,2
REDD	*SSP2 default*	*-135,8*	*96,6*	*-55,9*	*-176,6*
	SSP2 food low	-183,8	74,6	-80,6	-177,7
	SSP2 tc costs low	-217,7	61,2	-99,8	-179,1
	SSP2 tc costs high	-92,0	143,6	-59,6	-176,0
	SSP2 C Price low	-119,6	124,3	-67,2	-176,7
All	*SSP2 default*	*-191,4*	*18,4*	*-29,4*	*-180,3*
	SSP2 food low	-191,5	18,5	-29,7	-180,3
	SSP2 tc costs low	-209,3	16,5	-44,6	-181,2
	SSP2 tc costs high	-175,4	26,6	-20,9	-181,1
	SSP2 C Price low	-139,5	85,1	-46,7	-177,9

Table SI-2: Sensitivity analysis for (a) lower demand for livestock products (SSP food low) (b) lower (SSP tc costs low) and (b) higher (SSP2 tc costs high) costs for agricultural yield increases and (c) lower tax on terrestrial carbon emissions (SSP2 C Price low) in comparison to the SSP2 default case. The sensitivity is tested for cumulative carbon emissions ($GtCO_2$) from deforestation and other land use change (LUC), cumulative uptake of carbon from regrowth of secondary natural vegetation on abandoned agricultural land (Regrowth) and cumulative carbon dynamics driven by climate change and CO_2 fertilization (CC & CO_2f). Cumulative carbon dynamics until 2100 are reported as mean values across all GCM specific results.

3. Model validation

In order to test our results, we compare regional MAgPIE projections for cropland and pasture with historical land use data (Klein Goldewijk et al., 2011) (Figures SI-5, SI-6). Deviations of regional MAgPIE cropland in 1995 from historical data stay below 8% and deviations in regional pasture area are below 12%. The near term trend in the MAgPIE cropland projections is in general similar to historical trends except for ASIA where cropland growth in MAgPIE stagnates until 2020. Near term pasture dynamics in ASIA, MAF, OECD and REF are similar to the historical pattern. LAM exhibits slightly declining pasture area in the future while in the historical period, increases were observed.

We report yield growth due to improved agricultural management and technological change by calculating a regional yield index (1995=100) (Figure SI-7). Due to investments into agricultural research and development, the regional yield level in our projections increases on average by ~15 - 20 points per decade in MAF depending on the scenario. In ASIA, yields increase by 8 to 10 points per decade and LAM exhibits yield increases by 5 to 7 points per decade. In OECD and REF, average yield increases stay below 4 points per decade. Historical data from Dietrich et al. (2012) shows yield increases due to technological change by ~14 points per decade after 1960. Fischer & Edmeades (2010) find that yields for the important food crops maize, rice and wheat increased at about 8 to 16 points per decade between 1988 and 2007. Historical corn yield levels in the USA increased at ~14 points per decade between 1960 and present (Egli, 2008). Thus, our productivity pathway is largely compatible with the historical trend.

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Finally, we compare global CO_2 emissions from land use change with the outcome of a model comparison covering four estimates for carbon emissions from LULCC (Houghton et al. 2012). CO_2 emissions in 2005 are very close to mean emissions reported by Houghton et al. The trend in emissions simulated by MAgPIE is similar to historical trends, reporting in general a decrease of emissions over time (Figure SI-8).

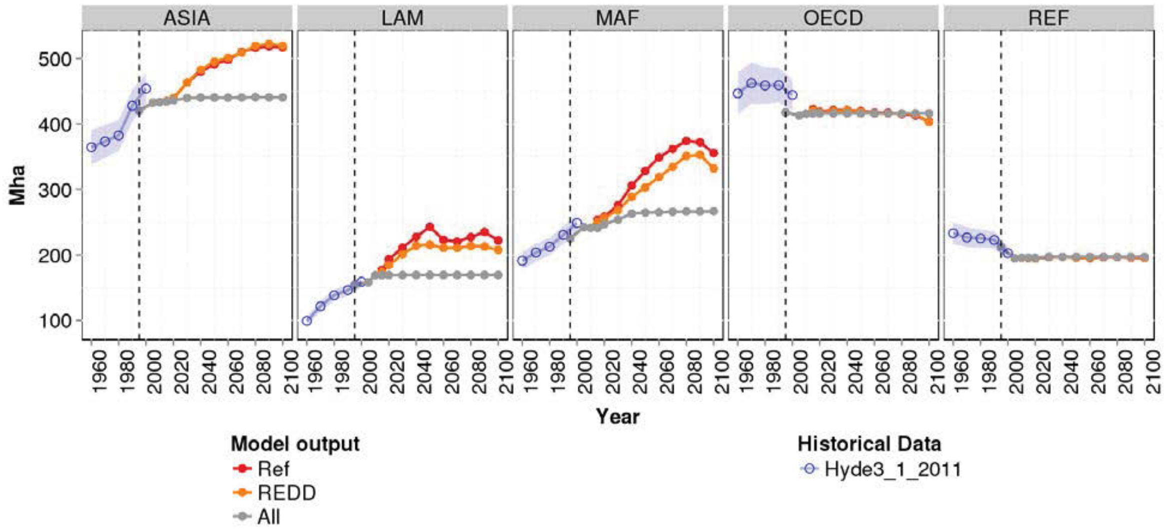

Figure SI-5 Regional cropland development under the Ref (red line), REDD (orange line) and All (grey line) scenarios until 2100 (mean over 5 GCMS). Estimates of historical cropland by Klein Goldewijk et al., 2011 for comparison. A vertical dashed line marks the start of the simulation period.

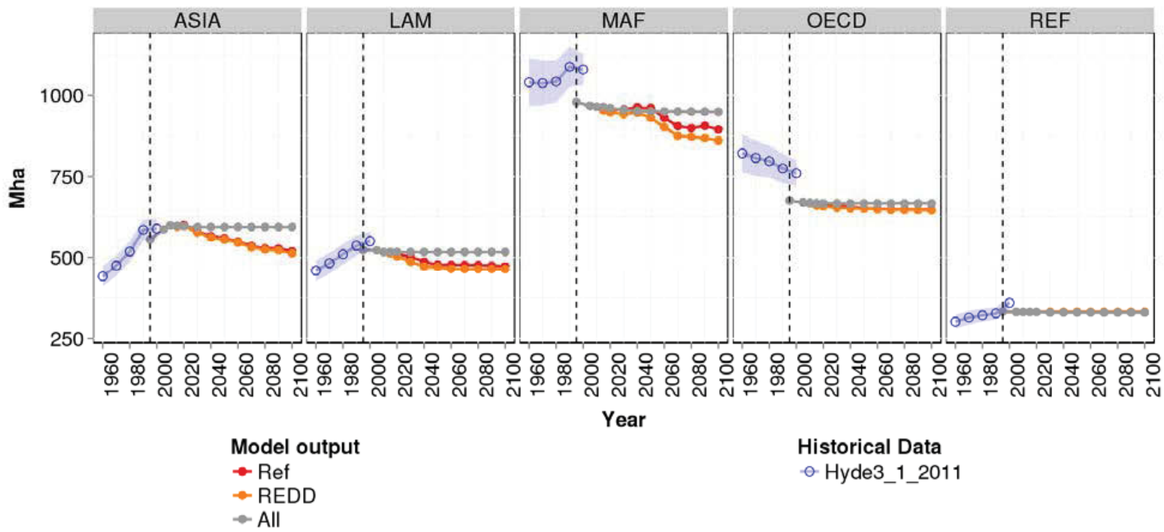

Figure SI-6 Regional pastureland development under the Ref (red line), REDD (orange line) and All (grey line) scenarios until 2100 (mean over 5 GCMS). Estimates of historical pasture area by Klein Goldewijk et al., 2011 for comparison. A vertical dashed line marks the start of the simulation period.

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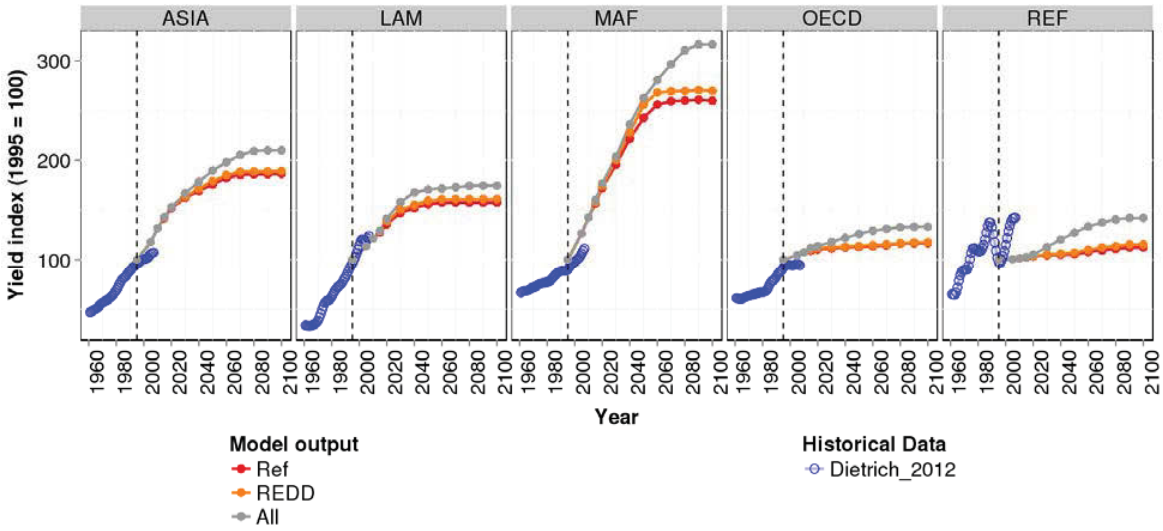

Figure SI-7 Regional yield index (1995 = 100) for the REF (red line), REDD (orange line) and ALL (grey line) scenarios until 2100 (mean over 5 GCMs). Increases over the simulation period reflect investments into yield increasing technological change (TC). Historical data from Dietrich et al. (2012). A vertical dashed line marks the start of the simulation period.

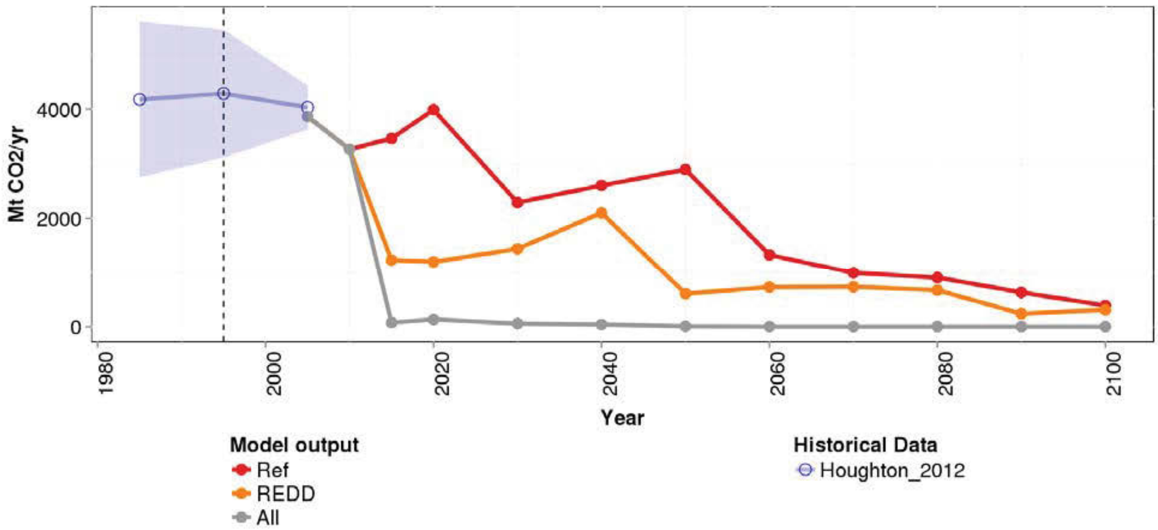

Figure SI-8: Global carbon emissions from land use change for the Ref (red line), REDD (orange line) and All (grey line) scenarios until 2100 (mean over different GCMS) compared to historical data from Houghton et al. (2012). The blue shaded region corresponds to the uncertainty range of the Houghton_2012 estimate. The vertical dashed line marks the start of the simulation period.

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4. Additional model description

4.1. MAgPIE (Model of Agricultural Production and its Impact on the Environment)

The global land-use model MAgPIE (Lotze-Campen et al., 2008, 2009, Popp et al. 2010) is a recursive dynamic optimization model with a cost minimization objective function, which has been coupled to the grid-based dynamic global vegetation model LPJmL (Bondeau et al., 2007, Müller and Robertson 2014). MAgPIE takes regional economic conditions such as demand for agricultural commodities and production costs as well as spatially explicit data on potential crop yields, carbon densities, water availability (from LPJmL) and land into account and derives specific land use patterns, yields and total costs of agricultural production for each grid cell. Due to computational constraints all spatially explicit data with 0.5 degree resolution (59,199 grid cells) is aggregated to 600 simulation units in this study based on a hierarchical bottom-up clustering algorithm (Dietrich et al. 2013).

MAgPIE simulates land-use activities using five land-use classes: cropland, pasture, forest, urban areas (which is a static area), and other land. Input data for each land-use class enters MAgPIE on simulation unit level (Krause et al. 2013). Cropland input is calculated according to the methodology described in Fader et al. (2010) from the MIRCA2000 dataset (Portmann, Siebert, and Döll 2010). Pasture, forest and urban land is largely based on work by Erb et al. (2007). Applying a residual approach, Erb et al (2007) define pasture as the difference between the total area of a grid cell and the area allocated to the sum of the other land use classes, which results in a substantially larger extent of global grazing land as indicated by the FAO definition "Permanent meadows and pastures" (FAOSTAT 2013). To harmonize on FAO data, cellular pasture area based on 4 grazing suitability classes from Erb et al. (2007) is counted up, starting with the most suitable grazing class, until the regional FAO area is matched. Cell specific excess pasture area from there is added to the forest pool for the grazing suitability classes 1 and 2 (aboveground NPP more than 200 g C/m2) and to other land for the unproductive classes 3 and 4. Forest inputs contain the forestry category by Erb et al. (2007), unused pasture area as explained above and those parts of the unused category from the Erb et al. (2007) dataset that are covered by forest according to Bryant et al. (1997) and Greenpeace International (2005). Finally, other land comprises all land area in each grid cell that is not part of any other category. Based on this initialization, in 1995, global cropland area is 1445 mio ha, pasture land area 3262 mio ha, global forest area 4235 mio ha and global other land area 3963 mio ha. Since not all available land is suitable for cropping due to terrain- and agro-edaphic constraints (Fischer et al. 2002), we used the suitability index from Fischer et al (2002) to restrict land that can be converted to cropland (Krause et al. 2013).

LPJmL computes potential irrigated and non-irrigated yields for each crop within each grid cell as an input for MAgPIE. In case of pure rain-fed production, no additional water is required, but yields are generally lower than under irrigation. In addition, LPJmL has been applied a priori to simulate cell specific available water discharge under potential natural vegetation and its downstream movement according to the river routing scheme implemented in LPJmL. Then, if a certain area share is assumed to be irrigated in MAgPIE, additional water for agriculture is taken from available discharge in the grid cell. MAgPIE endogenously decides on the basis of minimizing the costs of agricultural production where to irrigate which crops.

The objective function of the land use optimization model is to minimize total cost of production for a given amount of regional food and bioenergy demand. Regional food energy demand is defined for an exogenously given population in 10 food energy categories. All demand categories are estimated separately for 10 world regions (see Figure SI-9, Table SI-2) and have to be met by the world crop production. Additionally, the regions have to produce a certain share of their demand domestically to account for trade barriers (Schmitz et al., 2012).

Four categories of costs arise in the model: production costs for livestock and crop production, yield increasing technological change costs, land conversion costs and intraregional transport costs. Production costs, containing factor costs for labour, capital, and intermediate inputs, are taken from GTAP (Narayanan and Walmsley, 2008). In order to increase total agricultural production, MAgPIE can either

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intensify production (yield-increasing technology, shifting from rainfed to irrigated crop production systems) or increase cropland through land expansion. The endogenous implementation of technological change (TC) is based on a surrogate measure for agricultural land use intensity (Dietrich et al., 2012). Investing in TC leads not only to yield increases but also to increases in agricultural land-use intensity, which in turn raises costs for further yield increases. The other alternative for MAgPIE to increase production is to expand cropland into non-agricultural land (Krause et al., 2009; Popp et al., 2011). Cropland expansion involves land conversion costs for every unit of cropland, which account for the preparation of new land and basic infrastructure investments. Land conversion costs are based on country-level marginal access costs generated by the Global Timber Model (GTM) (Sohngen et al., 2009). Moreover, land expansion in MAgPIE is restricted by intraregional transport costs which accrue for every commodity unit as a function of the distance to intraregional markets and the quality of the infrastructure. The data set is based on GTAP transport costs (Narayanan and Walmsley, 2008) and a 30 arc-second resolution data set on travel time to the nearest city (Nelson, 2008).

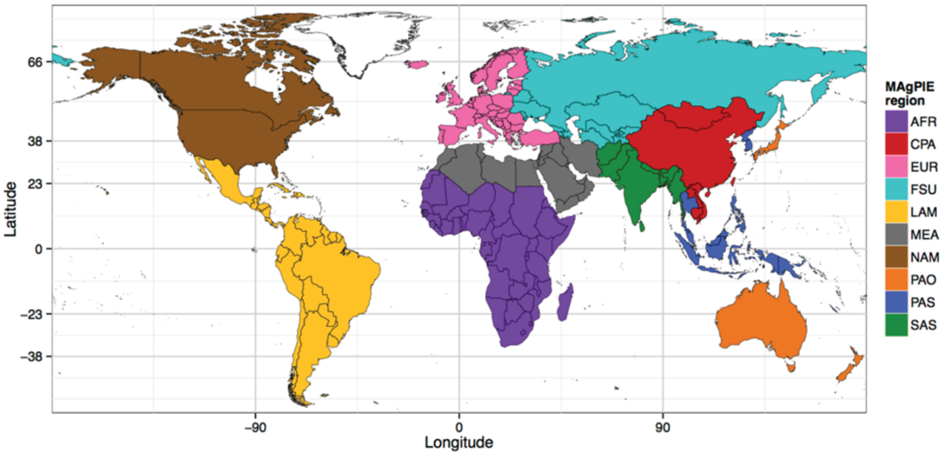

Figure SI-9: MAgPIE economic world regions.

MAgPIE	Region	SSP
AFR	Sub-Saharan Africa	MAF
CPA	Centrally planned Asia including China	ASIA
EUR	Europe including Turkey	OECD
FSU	States of the former Soviet Union	REF
LAM	Latin America	LAM
MEA	Middle East/North Africa	MAF
NAM	North America	OECD
PAO	Pacific OECD including Japan, Australia, New Zealand	OECD
PAS	Pacific (or Southeast) Asia	ASIA
SAS	South Asia including India	ASIA

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Table SI-3. Abbreviations and names of the 10 economic world regions in MAgPIE, and mapping to the 5 SSP regions used in figure SI-1

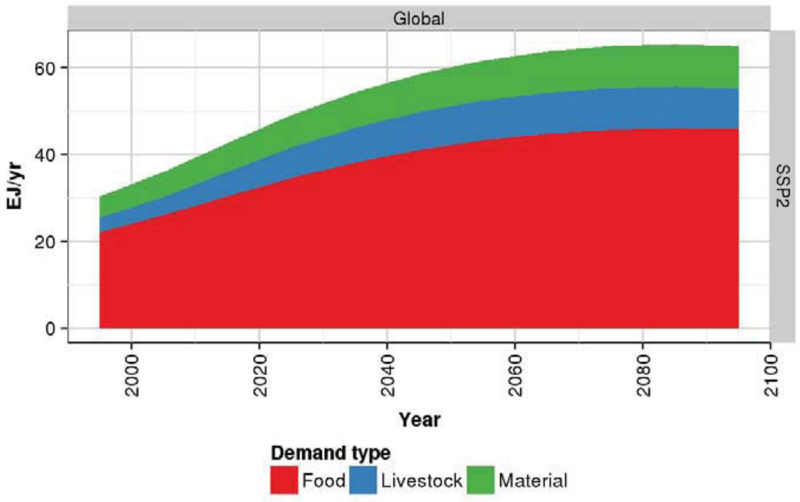

Figure SI-10: Time-series of food, livestock and material demand (based on population and GDP projections; IIASA 2013)

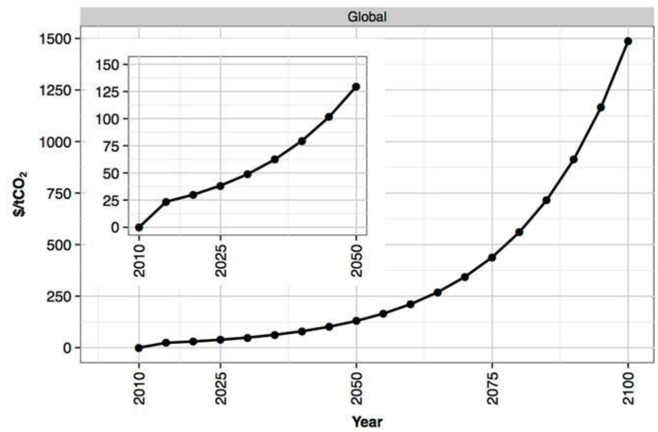

Figure SI-11: Time-series of assumed global tax on terrestrial carbon emissions between 2015 and 2100 in $/tCO_2$. The carbon tax has a level of 30 $/tCO_2$ in 2020, starts in 2015 and increases non-linearly at a rate of 5% per year (based on Kriegler et al. 2013).

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4.2. Detailed model description on carbon stocks and carbon dynamics

4.2.1. Carbon stocks

Simulated land types in MAgPIE are cropland, pasture, forest and other land (e.g. non-forest natural vegetation, abandoned land, desert). Each of them has cell-specific carbon densities for vegetation, soil and litter pools (see Figure SI-12). In the following we describe the parameterization for the carbon pools of each land type:

Forest - Forests are considered as natural vegetation in MAgPIE. Hence, vegetation, litter and soil carbon densities of forests are derived from the global hydrology and vegetation model LPJmL (Bondeau *et al* 2007, Müller and Robertson 2013) at grid-cell level. LPJmL simulates carbon densities (vegetation, litter and soil) for natural ecosystems under consideration of grid cell-specific temperature, precipitation and CO_2 concentration.

Other land - Vegetation, litter and soil carbon density of non-forest natural vegetation and deserts is derived from LPJmL at grid-cell level. Vegetation, litter and soil carbon densities of abandoned agricultural land are dynamic over time (see below).

Cropland – Vegetation carbon densities of cropland were derived by LPJmL, while litter carbon density is assumed to be 0. Due to soil management, croplands have lower soil organic matter than natural vegetation. To account for this, carbon stored in croplands is reduced depending on the climate zone by 20-52% (IPCC 2006; Chapter 5; Table 5.5) relative to natural soil carbon estimated by LPJmL (Bodirsky et al. 2012).

Pasture - Vegetation and litter carbon densities of pasture are derived from LPJmL at grid-cell level. As pastureland and natural vegetation have a similar level of soil organic matter (IPCC 2006; Chapter 6; Table 6.2) soil carbon densities of pastureland at the grid cell level were estimated using the natural vegetation carbon pools of LPJml.

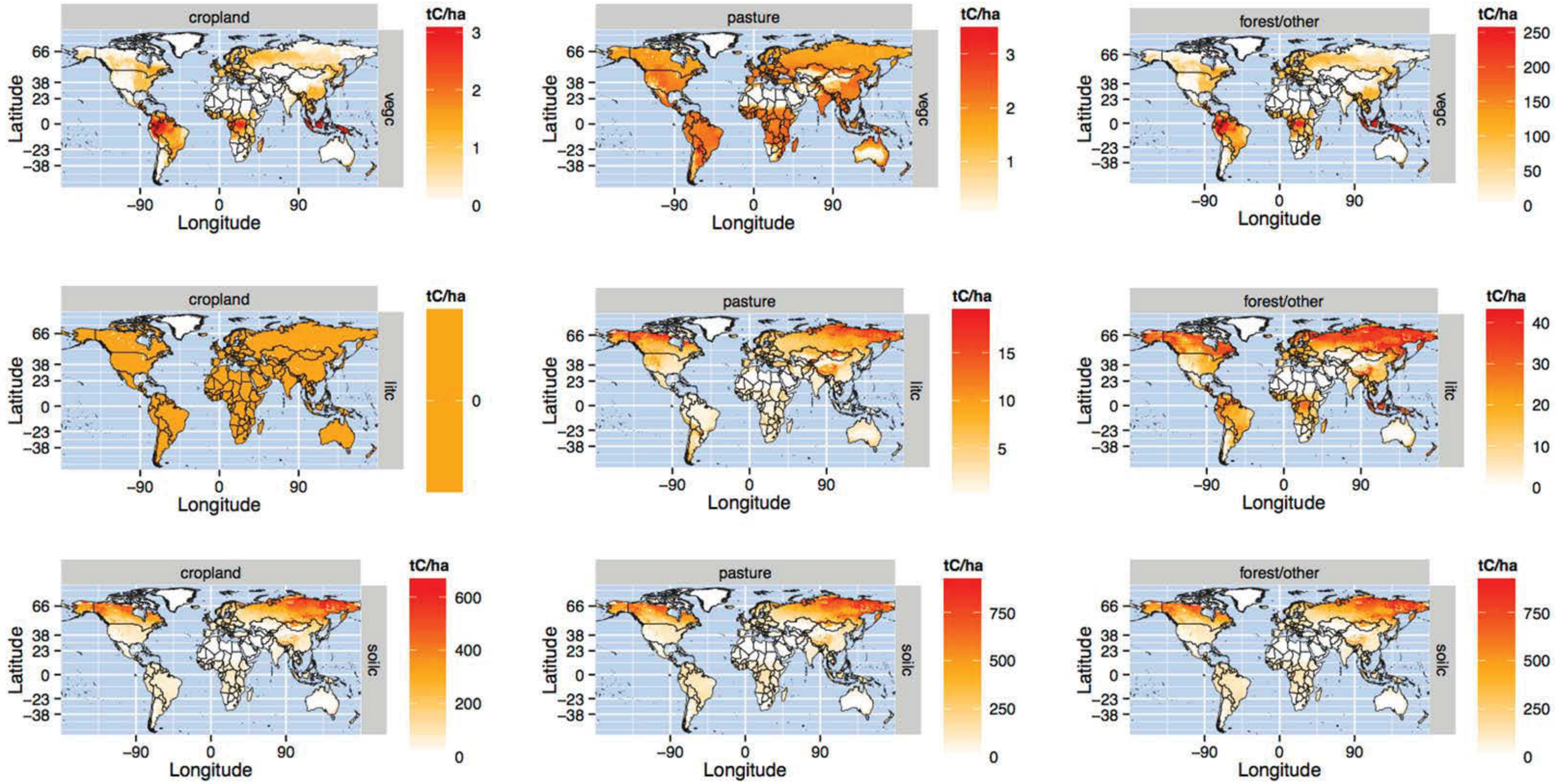

Figure SI-12: Carbon densities in 1995 (tC/ha) in MAgPIE simulated by LPJmL for each land type (cropland – left row; pasture – middle row; forest other natural vegetation – right row) and for each carbon pool (vegetation carbon - upper row; litter carbon – middle row; soil carbon – lower row).

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4.2.2. Carbon dynamics

In MAgPIE, carbon emissions from land use change occur if the carbon content of the previous land use activity exceeds the carbon content of the new land-use activity, but carbon stocks can also be affected by changing climatic conditions. Carbon emissions become negative if carbon stocks increase, for instance through regrowth of natural vegetation or CO_2 fertilization due to increased levels of CO_2 in the atmosphere.

Regrowth of natural vegetation
If agricultural land is abandoned, regrowth of natural vegetation takes place. Here, vegetation carbon density increases over time along S-shaped growth curves (Figure SI-13). The vegetation carbon density growth curves are based on a Chapman-Richards volume growth model (Murray and von Gadow 1993, Gadow and Hui 2001), which is parameterized using vegetation carbon density of natural vegetation (Figure SI-14) and climate region specific Mean Annual Increment (MAI) and MAI culmination age (IPCC 2006).

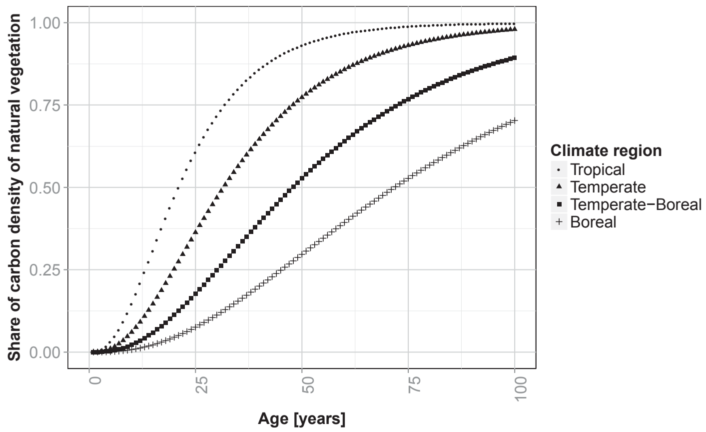

Figure SI-13: Climate region specific S-shaped regrowth curves for a period of 100 years. The vertical axis presents the share of grid-cell specific carbon density of potential natural vegetation in 1995 (Figure SI-14)

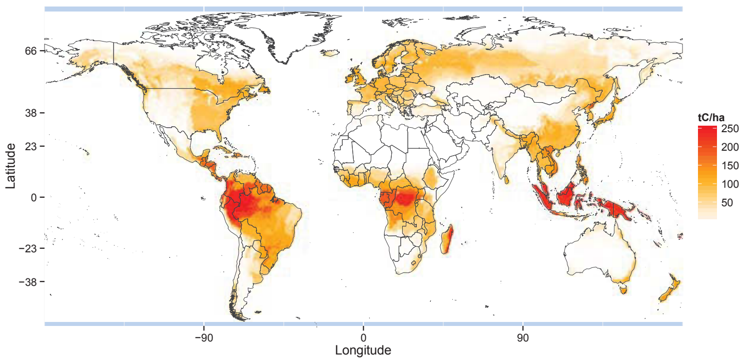

Figure SI-14: Grid-cell specific above- and belowground carbon density of potential natural vegetation in 1995 (tC/ha) derived from LPJmL used as input in Chapman-Richards volume growth model

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Litter and soil carbon density of abandoned agricultural land are assumed to increase linearly towards the value of forest/other vegetation (Figure SI-14) within a 20 year's time frame (IPCC 2000). The initial value for vegetation and litter carbon density is assumed to be 0, while the initial value for soil carbon density depends on the former land-use.

Climate change and CO_2 fertilization
Climate impacts in MAgPIE are represented by changes in biophysical inputs like crop yields, carbon densities and water availability, which are derived using the DGVM LPJmL. LPJmL is a dynamic vegetation, hydrology and crop model operating at a global grid (0.5 degree longitude/latitude). LPJmL simulates yields for the most important agricultural crops, and carbon densities (vegetation, litter and soil) for natural ecosystem under consideration of different climatic scenarios. To account for uncertainty in climate projections for RCP 2.6, we use in this study the five GCMs: HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M (Hempel et al. 2013). To facilitate comparison of MAgPIE results, GCM specific biophysical inputs derived from LPJmL are harmonized for the initial MAgPIE time step. Yield harmonization is achieved by defining a reference GCM (HadGEM2-ES) and multiplication of the relative changes (all time steps divided by initial time step) of all other GCMs with this reference. This method preserves the relative differences and assures that the input data is identical for the initial time step. For carbon densities, this approach leads to a distortion of the temporal dynamics compared to the original data. Therefore, GCM specific differences with respect to 1995 have been added to the 1995 reference value. Resulting negative values are set to 0 and values that exceed the maximum carbon density in the original data have been cut off. Changes in carbon densities are given as a mean (Figure SI-15) and standard deviation (Figure SI-16) across all GCMs for different carbon pools (vegetation, litter and soil) and land types.

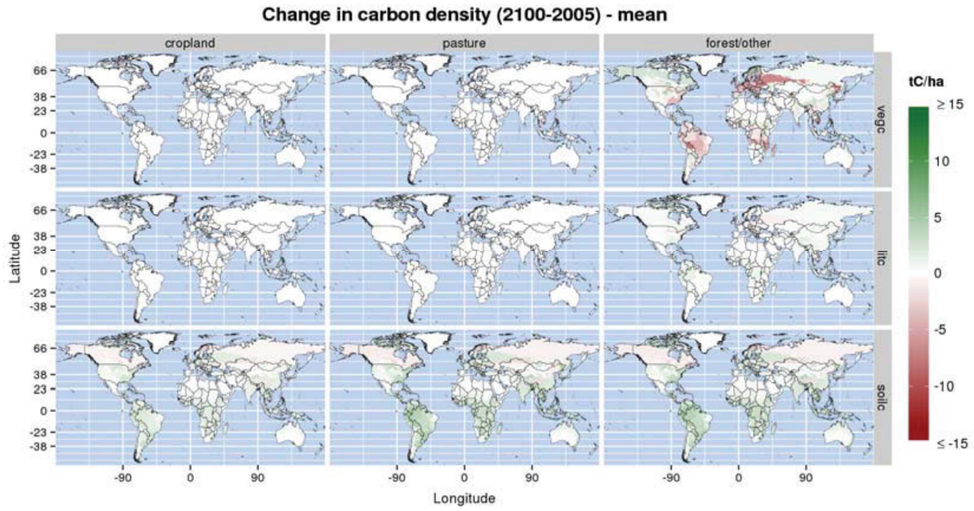

Figure SI-15 Mean change (2100 compared to 2005) in carbon densities (tC/ha) simulated by LPJmL across five applied GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M) based on climate projections for RCP 2.6. For each land type (cropland – left row; pasture – middle row; forest other natural vegetation – right row) and for each carbon pool (vegetation carbon - upper row; litter carbon – middle row; soil carbon – lower row).

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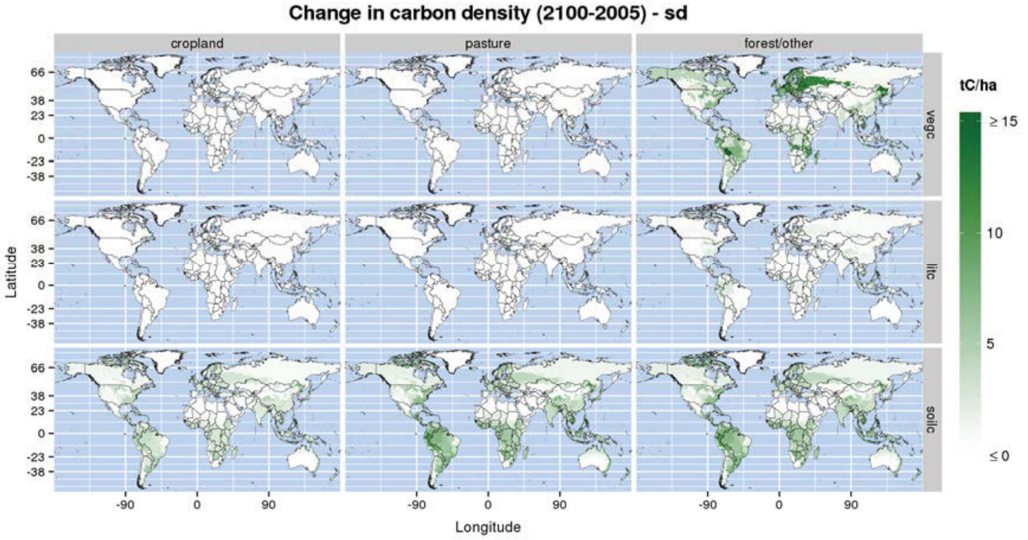

Figure SI-16: Standard deviation (2100 compared to 2005) from mean carbon densities (tC/ha) simulated by LPJmL across five applied GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M) based on climate projections for RCP 2.6. For each land type (cropland – left row; pasture – middle row; forest other natural vegetation – right row) and for each carbon pool (vegetation carbon - upper row; litter carbon – middle row; soil carbon – lower row).

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III The global economic long-term potential of modern biomass in a climate-constrained world*

Authors:
David Klein, Florian Humpenöder, Nico Bauer, Jan Philipp Dietrich, Alexander Popp, Benjamin Leon Bodirsky, Markus Bonsch and Hermann Lotze-Campen

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The global economic long-term potential of modern biomass in a climate-constrained world

David Klein, Florian Humpenöder, Nico Bauer, Jan Philipp Dietrich, Alexander Popp, Benjamin Leon Bodirsky, Markus Bonsch and Hermann Lotze-Campen

Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany

E-mail: david.klein@pik-potsdam.de

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Abstract

Low-stabilization scenarios consistent with the 2 °C target project large-scale deployment of purpose-grown lignocellulosic biomass. In case a GHG price regime integrates emissions from energy conversion *and* from land-use/land-use change, the strong demand for bioenergy and the pricing of terrestrial emissions are likely to coincide. We explore the global potential of purpose-grown lignocellulosic biomass and ask the question how the supply prices of biomass depend on prices for greenhouse gas (GHG) emissions from the land-use sector. Using the spatially explicit global land-use optimization model MAgPIE, we construct bioenergy supply curves for ten world regions and a global aggregate in two scenarios, with and without a GHG tax. We find that the implementation of GHG taxes is crucial for the slope of the supply function and the GHG emissions from the land-use sector. Global supply prices start at \$5 GJ^{-1} and increase almost linearly, doubling at 150 EJ (in 2055 and 2095). The GHG tax increases bioenergy prices by \$5 GJ^{-1} in 2055 and by \$10 GJ^{-1} in 2095, since it effectively stops deforestation and thus excludes large amounts of high-productivity land. Prices additionally increase due to costs for N_2O emissions from fertilizer use. The GHG tax decreases global land-use change emissions by one-third. However, the carbon emissions due to bioenergy production increase by more than 50% from conversion of land that is not under emission control. Average yields required to produce 240 EJ in 2095 are roughly 600 GJ ha^{-1} yr^{-1} with and without tax.

S Online supplementary data available from stacks.iop.org/ERL/9/074017/mmedia

Keywords: biomass, climate change mitigation, land use, resource potential, biomass supply curve, carbon tax, energy

1. Introduction

Energy from biomass as a substitute for fossil energy is not only supposed to improve energy security. Several studies investigating the transition of the energy system under climate change stabilization targets consider bioenergy a large-scale and cost-effective mitigation option (Riahi *et al* 2007, Calvin *et al* 2009, Luckow *et al* 2010, Van Vuuren *et al* 2010a, Rose *et al* 2013). In particular, bioenergy with CCS (BECCS) may significantly reduce stabilization costs, since its negative emissions compensate emissions from other sources and across time (Van Vuuren *et al*, 2010b, 2013, Kriegler *et al* 2013, Azar *et al* 2010, 2013, Klein *et al* 2013). The amount of realizable negative emission directly depends on the amount of biomass available. Thus, the biomass potential and its cost become crucial factors that affect overall mitigation costs (Rose *et al* 2013, Klein *et al* 2013). While the scientific consensus on the importance of bioenergy for climate change mitigation is strong (Rose *et al* 2013), high uncertainties remain regarding the biomass potential, resulting in wide ranges of estimates (28–655 EJ yr^{-1}, see also section 2). This is mainly due to uncertainties about future developments of agricultural yields[1], demand for food and feed, and availability of land and water for agricultural production. In particular, there are only a few global studies attributing costs or prices to the estimated bioenergy potential (see also section 2). The purpose of this study is to provide supply price curves for lignocellulosic biomass that can serve as a basis for the economic assessment of bioenergy in climate change mitigation scenarios.

Low-stabilization scenarios consistent with the 2 °C target project large-scale deployment of biomass necessitating dedicated production of modern lignocellulosic biomass at levels that exceed the potential of residues and first-generation biofuels (Popp *et al* 2013). Therefore, this study focuses on purpose-grown lignocellulosic and herbaceous biomass. A major concern about the sustainability of large-scale bioenergy production is its potential to induce deforestation. First, deforestation causes carbon emissions and counteracts the objective of emission mitigation if no effective forest protection regime is in place (Wise *et al* 2009, Popp *et al* 2011a, 2012, Calvin *et al* 2013). Second, deforestation entails substantial biodiversity loss, as forests are the most biologically diverse terrestrial ecosystems (Turner 1996, Hassan *et al* 2005). Both adverse effects could be considerably mitigated if GHG emissions from the land-use sector (including non-CO_2 emissions such as N_2O from fertilizer use) were equally priced with energy emissions. In the case of a GHG price regime comprising energy *and* land-use/land-use change emissions, the strong demand for bioenergy and pricing of terrestrial emissions are likely to coincide, and the GHG pricing is likely to affect the availability and productivity of land for bioenergy, and thus bioenergy prices for a given level of demand. However, to our knowledge the available literature on bioenergy potentials does not consider GHG pricing in the land-use sector (Hoogwijk 2004, Hoogwijk *et al* 2005, 2009, Smeets *et al* 2007, Erb *et al* 2009, Van Vuuren *et al* 2009, Dornburg *et al* 2010, Haberl *et al* 2010, Beringer *et al* 2011a). Therefore, this study investigates the impact of GHG prices on the potential and the supply prices of bioenergy.

Furthermore, these studies assume bioenergy production only on land not required for food production, and they assume yield improvements to be independent of bioenergy demand. However, these assumptions may not hold if the demand for bioenergy strongly increases, as projected by low-stabilization scenarios. In contrast, the approach applied for this study incorporates land competition between bioenergy and other crops. Moreover, it allows derivation of yield improvement rates required to satisfy given levels of bioenergy and food demand, since technological development is endogenous in this approach. Using the land-use optimization model MAgPIE (Model of Agricultural Production and its Impacts on the Environment) (Lotze-Campen *et al* 2008, Popp *et al* 2010), we construct bioenergy supply curves for ten world regions by measuring the bioenergy price response to different scenarios of bioenergy demand and GHG prices. The model endogenously treats the trade-off between land expansion (causing costs for land conversion and for resulting carbon emissions) and intensification (requiring investments for research and development) by minimizing the total agricultural production costs. GHG emissions from the land-use system are priced, and resulting costs for emissions accruing from bioenergy production are reflected in bioenergy prices.

The purpose of this study is to quantitatively assess the global economic potential of lignocellulosic purpose-grown biomass under different climate policy proposals. It presents bioenergy supply price curves on a regional level. Two key questions are addressed: what is the global potential of purpose-grown second-generation biomass and how are potential and corresponding supply prices dependent on GHG taxes?

2. Present bioenergy potential studies

It is important to note that this study focuses on second-generation biomass. The literature about first-generation biomass is larger, but not a concern here. Several studies have investigated the global potential of second-generation purpose-grown bioenergy under different constraints. There are mainly two types of global bioenergy potential study so far. The first group identifies the potential of bioenergy by defining the area of land available for bioenergy production and by making assumptions about the productivity of this land (Hoogwijk *et al* 2005, Smeets *et al* 2007, Erb *et al* 2009, 2012, Van Vuuren *et al* 2009, Dornburg *et al* 2010, Haberl *et al* 2010, 2013, Smith *et al* 2012, Beringer *et al* 2011a). These studies assume some kind of food-first policy, as they exclude land that is needed for food and feed production and allow bioenergy production only on land that is not used for food production or might in future become available due to intensification or decreasing demand for agricultural commodities. The development of technological change is included in these studies by exogenous assumptions on food and feed crop yield growth that largely determine the land available for bioenergy production. Other important factors are food demand, trade, and livestock production. Some studies consider additional sustainability constraints by excluding land for forest and nature conservation or due to water scarcity or degradation (Van Vuuren *et al* 2009, Beringer *et al* 2011a). Based on these studies, the estimates of the purpose-grown biomass potential for 2050 range from 28–265 EJ yr^{-1} at the lower end to 128–655 EJ yr^{-1} at the upper end[2].

The wide range can be explained by different assumptions on food demand, availability of land, and development

[1] In particular, there is lack of experience with the production of lignocellulosic feedstock for energy purposes, since it has not been produced on a commercial scale yet.

[2] This range excludes results from Smeets (2007), who reports a potential of 215–1272 EJ yr^{-1} in 2050 assuming large land area with high productivity.

of yields, which are identified by these studies as the main determinants of the bioenergy potential. Low estimates are mainly driven by assuming high population growth (resulting in high food demand) and excluding water scarce areas and nature conservation areas, resulting in low availability of land for bioenergy production. Projected future yields are another crucial (yet highly uncertain) parameter determining the bioenergy potential. Haberl *et al* 2010 report a wide range of 7–60 GJ ha^{-1} yr^{-1} used in the literature. The estimates at the upper end of bioenergy potentials are mainly based on high-yield growth rates for food and bioenergy crops over the next decades that are at present level or higher (Hoogwijk *et al* 2005, Van Vuuren *et al* 2009, Smeets *et al* 2007, Dornburg *et al* 2010).

These studies use simulation models to project the future development of the land-use system and feature different levels of spatial explicit biophysical conditions. The projections applying average yields over large areas considered suitable for bioenergy production tend to project high bioenergy potentials, 120–660 EJ yr^{-1} (Hoogwijk *et al* 2005, Van Vuuren *et al* 2009, Smeets *et al* 2007, Dornburg *et al* 2010), while process-based studies that aim to include spatially explicit data on local biophysical conditions estimate lower ranges, 37–141 EJ yr^{-1} (Beringer *et al* 2011b, Erb *et al* 2009, 2012). Another approach derives the actual net primary productivity (NPP) from satellite data and argues that the NPP poses an upper bound to bioenergy production. The estimates reported by these studies (excluding residues) are 121 (Smith *et al* 2012) and 190 (Haberl *et al* 2013).

However, to be able to assess the economic potential and hence the competitiveness of bioenergy in the energy system, one needs information about the supply costs of biomass. Therefore the second group of studies additionally assigns costs for bioenergy production to the different types of land cell and constructs supply cost curves by sorting the cells by their biomass production costs. Only a few studies provide information about the production costs, particularly concerning second-generation bioenergy on a global scale (Hoogwijk 2004, Hoogwijk *et al* 2009, Van Vuuren *et al* 2009). Hoogwijk (2009) introduces costs for land, capital, and labor to the technical potential identified in Hoogwijk (2005) and finds that 130–270 EJ yr^{-1} in 2050 may be produced at costs below \$2.2 GJ^{-1} and 180–440 EJ yr^{-1} below \$4.5 GJ^{-1} [3]. The underlying scenarios assume significant land productivity improvements and cost reductions due to learning and capital–labor substitution. Using a similar approach (but assuming less available land due to a lower accessibility factor), Van Vuuren *et al* (2009) excludes further areas from biomass production due to biodiversity conservation, water scarcity, and land degradation. This reduces the global biomass potential in 2050 from 150 EJ yr^{-1} without these land constraints to 65 EJ yr^{-1}. Following the same cost approach as Hoogwijk (2005), Van Vuuren *et al* (2009) finds that in 2050 about 50 EJ could be produced at costs below \$2.2 GJ^{-1} and 125 EJ below \$4.8 GJ^{-1}. Realizing the full potential of 150 EJ by taking biomass from degraded land into account would cost up to \$8 GJ^{-1}. Both studies allow bioenergy production on abandoned and rest land only and consider only woody bioenergy crops.

[3] Dollars are given as US \$2005 in this study. Dollars from other years are converted using the consumer price index http://oregonstate.edu/cla/polisci/sites/default/files/faculty-research/sahr/inflation-conversion/excel/cv2008.xls

3. Methods

3.1. The land-use model MAgPIE

MAgPIE is a spatially explicit, global land-use optimization model (Lotze-Campen *et al* 2008, Popp *et al* 2010). The objective function of MAgPIE is the fulfillment of food, livestock, material, and bioenergy demand at least costs under socio-economic, political, and biophysical constraints. Demand is income elastic, but price-induced changes in demand are not reflected. Major cost types in MAgPIE are factor requirement costs (capital, labor, and fertilizer), land conversion costs, transportation costs to the closest market, investment cost for technological change (TC), and costs for GHG emission rights. The cost minimization problem is solved in 10-year time steps until 2095 in recursive dynamic mode by varying the spatial production patterns, by expanding crop land, and by investing in yield-increasing TC (Lotze-Campen *et al* 2010, Dietrich *et al* 2012). TC increases the potential yields of all crops within a region by the same factor. The costs for enhancing the yields in a specific region increase with the level of agricultural development of the particular region; i.e., the higher the actual yields in a region the higher the costs for one additional unit of yield increase (Dietrich *et al* 2014). The model distinguishes ten economic world regions with global coverage (cf supplementary material section S1.2): Sub-Saharan Africa (AFR), Centrally Planned Asia including China (CPA), Europe including Turkey (EUR), states of the former Soviet Union (FSU), Latin America (LAM), Middle East/North Africa (MEA), North America (NAM), Pacific OECD including Japan, Australia, New Zealand (PAO), Pacific (or Southeast) Asia (PAS), and South Asia including India (SAS). MAgPIE considers spatially explicit biophysical constraints such as crop yields and availability of water (Bondeau *et al* 2007, Müller and Robertson 2013) and land (Krause *et al* 2013) as well as socio-economic constraints such as trade liberalization, forest protection, and GHG prices.

MAgPIE differentiates between the land types cropland, pasture, forest, and other land (e.g. non-forest natural vegetation, present and future abandoned land, desert). Unlike the cropland sector, which is subject to optimization, the areas in the pasture sector, the forestry sector, and parts of forestland (mainly undisturbed natural forest within protected forest areas, FAO 2010) are fixed at their initial value in this study. Considering this, about 7900 Mha (~61%) of the world's land surface is freely available in the optimization of the initial time step, of which about 3000 Mha are suitable for cropping. Since all crops including bioenergy have equal access to the available land (no underlying food-first policy), the resulting competition for land is reflected in shadow-prices for bioenergy derived from the demand-balance equation. As we consider bioenergy crops to be a globally tradable good, emerging bioenergy prices are equal across regions. However, interregional bioenergy transport as such is not considered.

Yields of dedicated grassy and woody bioenergy crops (rainfed only) obtained from the vegetation model LPJmL (Beringer *et al* 2011a, Bondeau *et al* 2007) represent yields achieved under the best available management options. Since MAgPIE aims to represent actual yields in its initial time step, these yields are downscaled using information about observed land-use intensity (Dietrich *et al* 2012) and FAO yields (FAO 2013). For instance, in AFR yields are reduced by about 70% (supplementary material figure S12). However, by investing in yield increasing technologies this yield gap can be closed, and technological progress over a long time can even increase yields beyond LPJmL yields since it pushes the technology frontier.

MAgPIE calculates emissions of the Kyoto GHGs carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) (Bodirsky *et al* 2012, Popp *et al* 2010, 2012). Carbon emissions from land conversion occur if the carbon content (aboveground and belowground vegetation carbon) of the new land type is lower than the carbon content of the previous land type (e.g. if forest is converted to cropland). The amount of carbon stored differs across land types and the values are derived from LPJmL. Soil carbon and decay time of onsite biomass are not considered, whereas the regrowth of natural vegetation on abandoned land and the resulting increase of its carbon stock are considered. Costs accruing due to the taxation of emissions are added to the production costs. Thus, the GHG tax incentivizes the reduction of emissions resulting from land-use change (CO_2) and agricultural production (N_2O, CH_4). It is important to note that in our analysis carbon emissions from all types of land conversion are accounted for and reported in the results, but only carbon emissions from deforestation (conversion of forest land into any other land type) are taxed. We consider this type of carbon tax regime to be closest to a REDD scheme (reducing emissions from deforestation and forest degradation, Ebeling and Yasué 2008), which is currently discussed by the international community and expected to contribute to a post-Kyoto emission reduction treaty (Phelps *et al* 2010). Agricultural N_2O and CH_4 emissions can be reduced according to marginal abatement cost curves based on the work of Lucas *et al* (2007) and Popp *et al* (2010).

3.2. Scenarios

The socio-economic assumptions regarding trade liberalization, forest protection, and demand for food, feed, and material are geared to the 'middle of the road' narrative of shared socio-economic development pathways (SSPs), with intermediate challenges for adaptation and mitigation (O'Neil *et al* 2012, see supplementary material for more information). The SSPs do not incorporate climate policy by definition. We simulate the outcome of climate policy by applying GHG taxes and bioenergy demand scenarios as exogenous parameters. While bioenergy demand is varied in order to derive the bioenergy supply price curves (see supplementary material), the GHG tax is varied for the sensitivity analyses of the supply curves.

The global uniform GHG tax on CO_2, N_2O, and CH_4 in the tax30 scenario starts in 2015 increasing by 5% per year (2020, \$30 tCO_2eq^{-1}, giving the scenario its name; 2055, \$165 tCO_2eq^{-1}; 2095, \$1165 tCO_2eq^{-1}). It is close to CO_2 prices required to reach low stabilization targets at 450 ppm CO_2eq (Rogelj *et al* 2013, IEA 2012a, Luderer *et al* 2013). The N_2O and CH_4 taxes are calculated from the CO_2 tax using the GWP100. In the tax0 scenario there is no GHG tax.

The bioenergy supply price curves are derived by measuring the price response of the MAgPIE model to 73 different global bioenergy demand scenarios. Each bioenergy demand scenario yields a time path of regional allocation of bioenergy production and global bioenergy prices. For each region and time step the supply curve was fitted to the resulting 73 combinations of bioenergy production and bioenergy prices (see supplementary material for details and data).

4. Results

4.1. Bioenergy prices

Figure 1 shows the globally aggregated supply curves for 2055 and 2095. Without a GHG tax in the land-use sector, bioenergy in 2055 can be supplied starting at \$5 GJ^{-1}. Introducing a global uniform GHG tax substantially increases supply prices for biomass by about \$2 GJ^{-1} at low bioenergy demands (below 30 EJ yr^{-1}) and \$5 GJ^{-1} at medium to high demands (above 120 EJ yr^{-1}) in 2055. In 2095 the tax increases bioenergy prices by \$10 GJ^{-1}.

Conditions of bioenergy production differ across regions, as do resulting bioenergy supply curves. Figure 2 shows the regional breakdown of the global supply curve for major producers. Without a GHG tax these are the tropical regions AFR and LAM (figure 1, bottom), which offer access to large areas of forest that can be converted to high-productivity land for crop and bioenergy production. This results in relatively flat supply curves in the tax0 scenario (figure 2, left). CPA and NAM contribute most of the remainder. There are only minor contributions from EUR, FSU, and PAS and almost none from PAO and MEA.

Introducing a GHG tax changes the relative position of the regional supply curves, since the consequences of pricing emissions are different across regions (figure 2, right). The price-elevating effect can be separated into two components: a steepening of the supply curve due to land exclusion and a translation effect due to non-CO_2 co-emissions from bioenergy (supplementary material figure S5). The steepening of the supply curve is caused by the component of the GHG tax that affects the carbon emissions from land conversion (CO_2 price), since it effectively stops deforestation (in 2055 and 2095) and thus reduces the amount of land available for the expansion of bioenergy production. The translation effect is caused by pricing nitrogen emissions that accrue from

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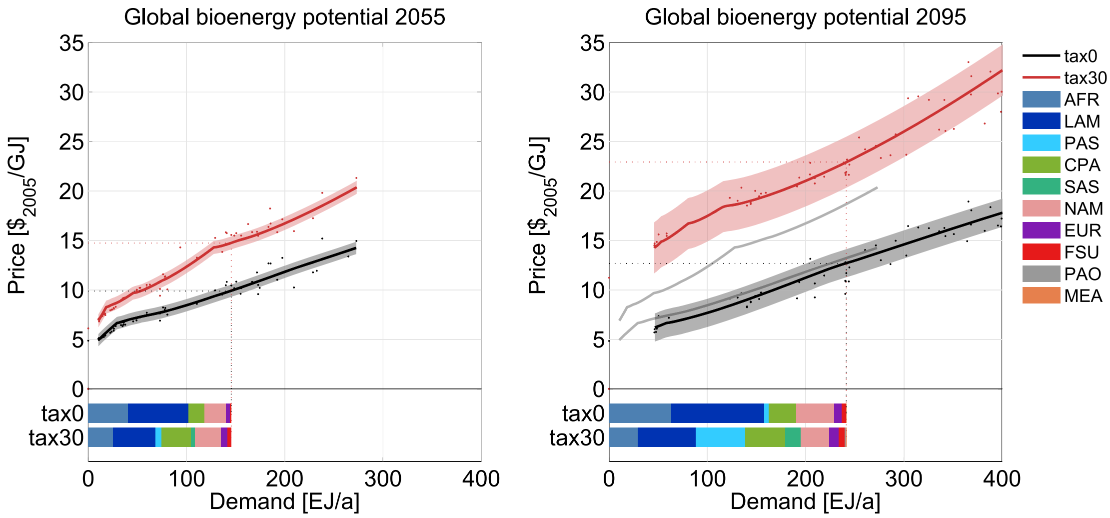

Figure 1. Globally aggregated bioenergy supply curves for 2055 (top left) and 2095 (top right) without (black line) and with a global uniform GHG tax (red line). The gray lines in the 2095 figure (right) indicate the positions of the 2055 supply curves. The colored bars at the bottom show the underlying regional bioenergy production pattern for the sample scenario (145 EJ in 2055 and 240 EJ in 2095). The shaded areas in the upper part indicate the standard deviation of the aggregated fit. Since the fit in 2095 is based on higher demand values than the 2055 fit, the absolute value of the spread is larger in 2095, as is the standard deviation.

fertilizer use for bioenergy crop cultivation. It does not scale with the bioenergy demand, since the amount of organic and inorganic fertilizer used per unit of bioenergy is constant.

The translation effect applies to the supply curves of all regions (supplementary material figure S6) and is stronger in 2095 than in 2055 since the GHG tax is substantially higher ($1165 versus $165 $tCOeq^{-1}$). Regions where no forest land is used in the tax0 scenario, such as CPA, PAS, and SAS, are only affected by this N_2O-price effect. The supply curves of regions that deforest in the tax0 scenario *additionally* show a steepening due to CO_2 pricing of forest land (strongest in AFR and LAM). The combined effects significantly increase regional supply prices and change the relative position of the supply curves (figure 2). This is reflected in the reallocation of the bioenergy production depicted at the bottom of figure 1: production shifts from AFR and LAM mainly to PAS, CPA, and SAS under the GHG tax. The tax makes PAS competitive, which features a relatively high but flat supply curve. The land restriction in PAS is not as strong as in other regions, since it can expand into productive land that is not under emission control (see below)[4].

4.2. Land and yields

To illustrate the effects of bioenergy demand and GHG tax on processes that drive the allocation and prices of bioenergy, such as changes in land cover, yields, and emissions, the remainder of the analysis focuses on the 2095 results of a medium bioenergy demand scenario selected as a sample out of the full portfolio (2055 results are included in the supplementary material). This is done to keep the analysis comprehensible. The characteristics of the effects observed in other demand scenarios are similar and qualitatively the same. To identify the effect of bioenergy production we compare results of this sample scenario to a zero-demand scenario (see supplementary material figure S4 for the respective scenarios and the full portfolio). Figure 3 shows the global land cover in 2095 and the initial value in 2005 for the four land types that are subject to optimization (top) and their changes from 2005 to 2095 (bottom). Figure 4 depicts the regional breakdown of the changes. Bioenergy production requires substantial amounts of land, almost 500 Mha for 240 EJ in 2095. With and without tax this is predominantly realized by crop land reduction (intensification) and usage of other land.

Without a GHG tax bioenergy causes only little additional deforestation (-55 Mha, in LAM mainly), since large amounts of accessible forest are already cleared for food and feed production (−250 Mha), (tax0 Bio versus tax0 NoBio). Bioenergy reduces cropland globally by 300 Mha (−17%) in 2095, mainly in AFR, LAM, CPA, and NAM. The increased usage of other land (−130 Mha) due to bioenergy production in the tax0 Bio scenario has two sources: increased conversion of existing other land (AFR) and usage of land that is abandoned in the tax0 NoBio scenario (LAM, EUR, FSU) (see also figure 4). Under the GHG tax, bioenergy and food production cannot access high-productivity forest land in AFR and LAM since it is effectively protected by the tax. Therefore, bioenergy plantations are partly pushed out of regions that formerly had access to forest (300 Mha in AFR and LAM). In parts this is compensated by further expansion into other land (−100 Mha), since resulting emissions are not penalized by the GHG tax. Substantial amounts of other land are converted in PAS that would have not been touched by the single effect of bioenergy *or* tax. The remaining part is compensated by the replacement of cropland with bioenergy cropland (−200 Mha), predominantly in SAS. Again, only the

[4] Under the GHG tax the global supply curves begin to flatten from the point where PAS becomes competitive.

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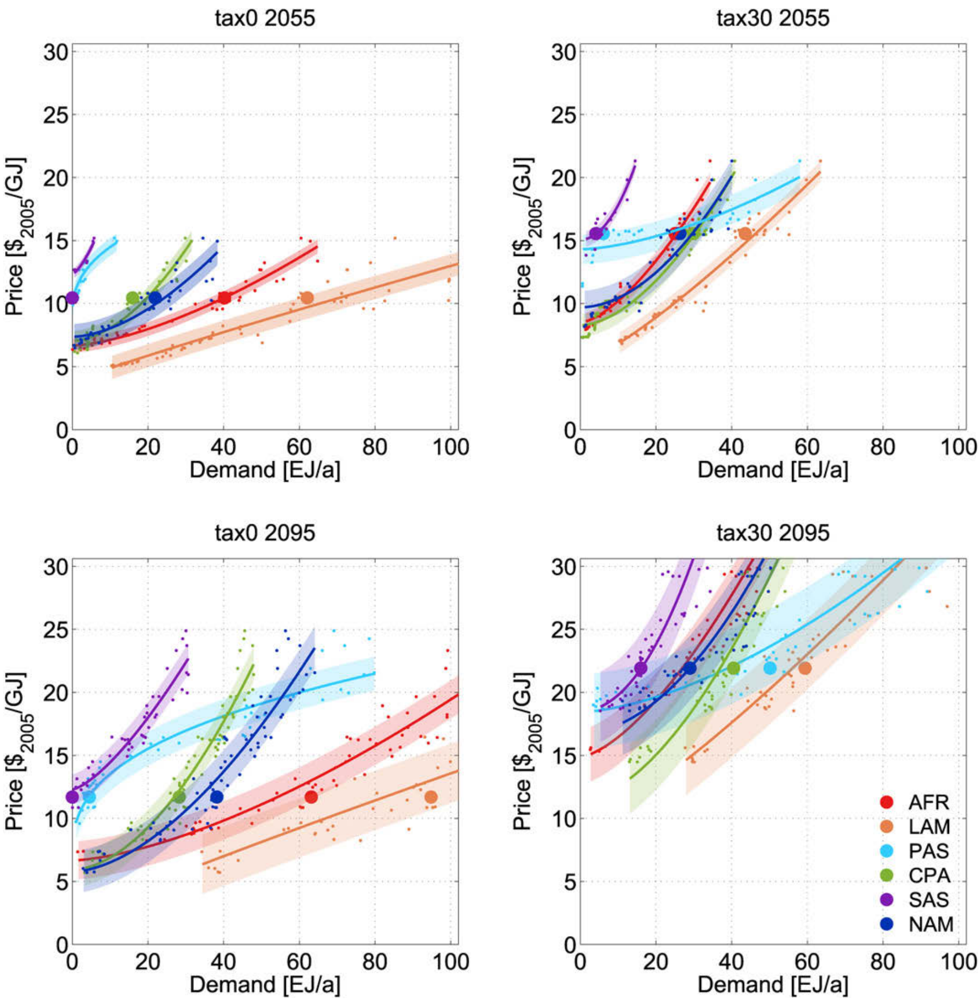

Figure 2. Impact of the GHG tax on the regional supply curves: regional breakdown of the global supply curve for major producers for the tax0 (left) and tax30 scenarios (right), and for 2055 (top) and 2095 (bottom) with the sample scenario marked. The shaded areas indicate the standard deviation of the fit. Since the fit in 2095 includes higher demands than the 2055 fit, the standard deviation is greater.

combination of bioenergy and tax leads to bioenergy production in SAS.

Bioenergy yields required for the global production of 240 EJ in 2095 vary substantially across regions and range from 80 GJ ha^{-1} yr^{-1} (FSU) to 690 GJ ha^{-1} yr^{-1} (LAM) in the tax0 scenario and 715 GJ ha^{-1} yr^{-1} (PAS) in the tax30 scenario (supplementary material figure S12). While the global average yield remains unchanged at 500 GJ ha^{-1} yr^{-1} (27 t ha^{-1} yr^{-1}), the GHG tax requires substantial yield increases for energy crops in all major producer regions, mostly in PAS (from 300 to 715 GJ ha^{-1} yr^{-1}), which compensates for the exclusion of productive land in AFR and LAM. If only major producers that cover more than 93% (224 EJ) of the global production (AFR, CPA, LAM, and NAM in the tax0 scenario and additionally PAS and SAS in the tax30 scenario) are taken into account, average yield increases from 596 to 611 GJ ha^{-1} yr^{-1} driven by the GHG tax[5]. The average yield of regions producing the remaining 17 EJ decreases from 157 to 136 GJ ha^{-1} yr^{-1}. Further information on yields can be found in the supplementary material.

[5] The difference from the global average is mainly due to FSU's low production on large areas of land.

4.3. Emissions

Figure 5 shows the carbon emissions from the land-use sector cumulated from 2005 to 2095 separated into emissions from food and energy crop production. Without the GHG tax, food production accounts for roughly 234 $GtCO_2$ (80%) of total emissions, mainly caused by deforestation in AFR (120 $GtCO_2$) and LAM (70 $GtCO_2$). Since the GHG tax almost stops deforestation, it substantially reduces carbon emissions from food crop production by 56% (to 102 $GtCO_2$). Remaining carbon emissions are caused by conversion of other land. The production of bioenergy causes additional emissions. If forest is not protected by the GHG tax, bioenergy emissions account for 63 $GtCO_2$, mainly due to deforestation in LAM (40 $GtCO_2$). Under the GHG tax there is no deforestation for bioenergy, but substantial expansion

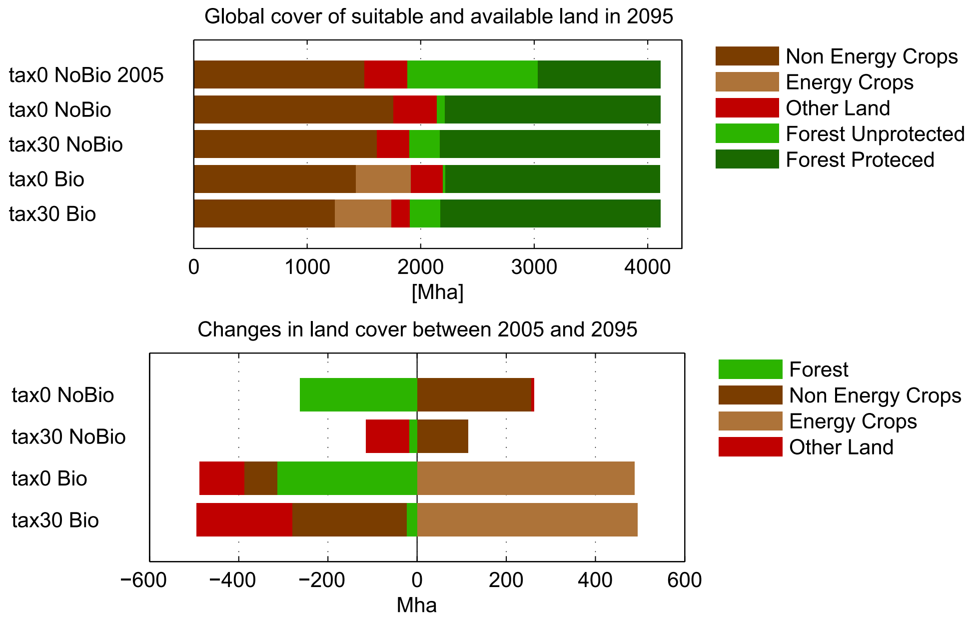

Figure 3. Global cover of land suitable and available (except protected forest) for agricultural production in 2095 with the initial value of 2005 (top). Global changes in land cover between 2005 and 2095 (bottom).

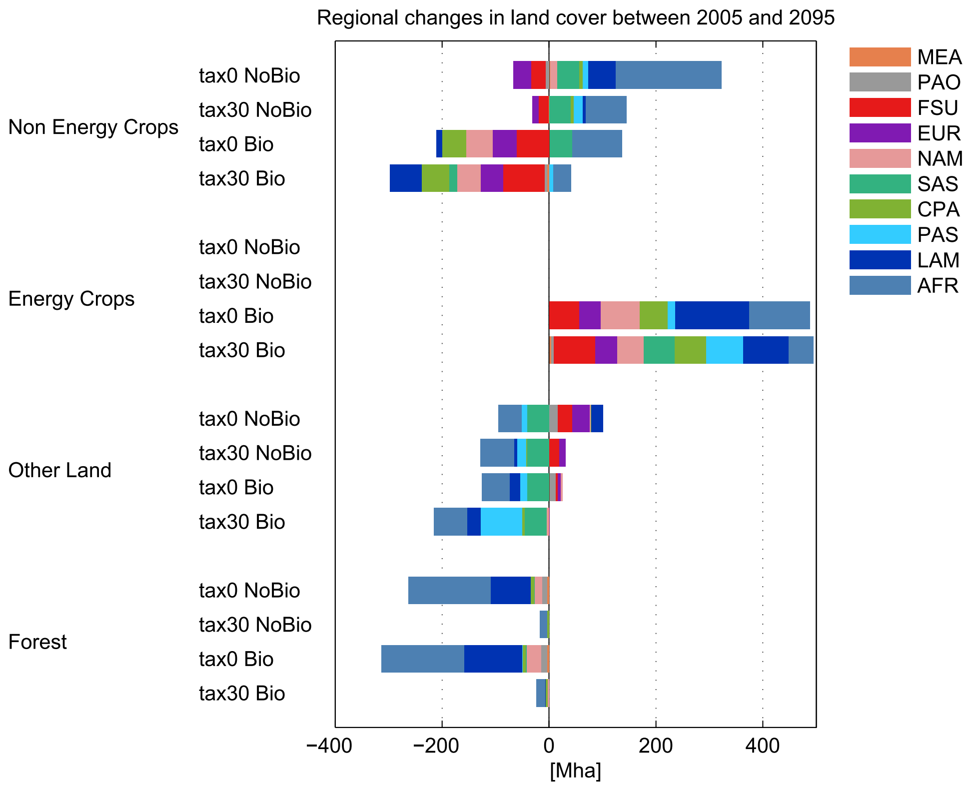

Figure 4. Breakdown of the global changes of land cover between 2005 and 2095 into regional changes.

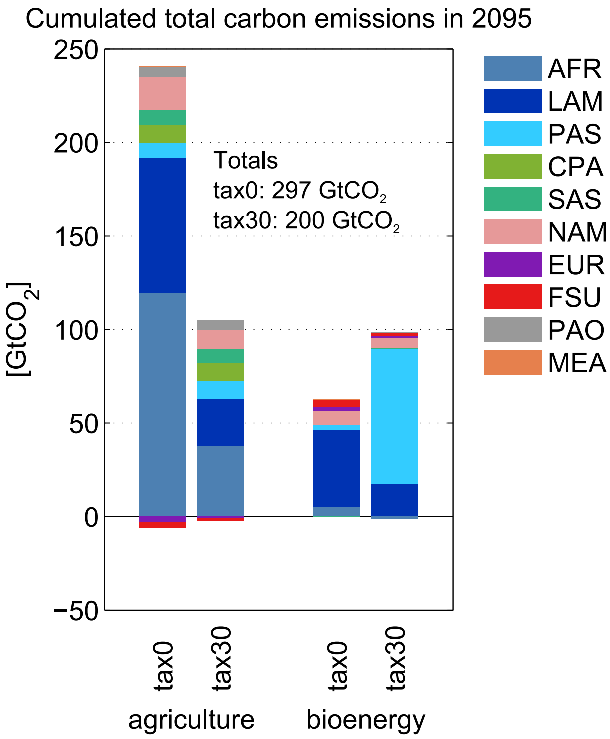

Figure 5. CO_2 emissions from land-use change due to bioenergy production and other agricultural activities cumulated from 2005 to 2095.

into other land[6], predominantly in PAS (73 $GtCO_2$). This leakage effect increases bioenergy emissions by 54% to 97 $GtCO_2$ cumulated from 2005 to 2095.

5. Discussion and conclusion

We constructed bioenergy supply curves for ten world regions and a global aggregate under full land-use competition using a high-resolution land-use model with endogenous technological change. We find that the implementation of GHG taxes for land-use and land-use change emissions is crucial for the slope of the supply function and the GHG emissions from the land-use sector.

Climate policy not only increases the demand for bioenergy, as several studies show (Rose *et al* 2013, Calvin *et al* 2009, Van Vuuren *et al* 2010a); it could also substantially increase supply prices of biomass raw material, as the present study shows (+\$5 GJ^{-1} in 2055, +\$10 GJ^{-1} in 2095). This is mainly due to the fact that large amounts of high-productivity forest land are *de facto* excluded by the GHG tax, since expanding into forests would entail substantial carbon emissions and related emission costs. Imposing the GHG tax thus prevents deforestation, lowers carbon emissions, reduces land available for bioenergy production, and increases the opportunity costs of land that is in competition with food production.

[6] In cases where bioenergy production inhibits or reverses regrowth of natural vegetation (other land), inhibited negative emissions are counted as positive emissions due to bioenergy production.

N_2O emissions from fertilizer use further increase bioenergy prices. The GHG tax also reduces the emissions in the case of no bioenergy demand, because the agricultural demand alone is a strong driver for cropland expansion. The bioenergy prices presented in this study emerge under full land-use competition with other crops and are therefore higher than pure production costs on abandoned land found by Hoogwijk *et al* (2009) and Van Vuuren *et al* 2009. The potential supply price of biomass raw material is a crucial parameter for the deployment of bioenergy. However, how much and along which conversion routes (e.g. fuels, electricity, heat) bioenergy might be deployed emerges from the balancing of supply and demand, the latter of which is crucially determined by emission reduction targets, carbon prices, biofuel mandates, and technology availability (Mullins *et al* 2014, Klein *et al* 2013, Rose *et al* 2013). Although bioenergy prices presented here may seem high compared to other energy carriers (4.6 \$2005 GJ^{-1} for coal in 2011, IEA 2012b), bioenergy supply at these prices could become relevant, since under climate policy the energy system shows high willingness to pay for bioenergy (Klein *et al* 2013). The incentive to pay high prices for bioenergy and to create negative emissions from it increases with the carbon price.

Results show that large-scale bioenergy production and high GHG prices, which are likely to coincide under a climate policy that embraces the energy and the land-use sector, can put substantial pressure on the land-use system. In the scenarios of this study bioenergy production requires large amounts of land, predominantly realized by intensification and increased usage of other land. Thus, two measures aiming at climate change mitigation (carbon taxes and bioenergy) could pose a threat to food security since they could dramatically reduce the land available for food production. Although not in the focus of this study, it is important to note that the resulting needs for intensification are likely to increase food prices. However, there is some indication that food-price effects of large-scale bioenergy production could be lower than price effects caused by climate change (Lotze-Campen *et al* 2013). Adding to a study by Wise *et al* (2009), who found substantial emissions from deforestation if terrestrial emissions are not priced at all (corresponding to the tax0 scenario used here), this study illustrates the potential consequences of a sectoral fragmented climate policy in the land-use sector: while effectively preventing deforestation the tax cannot prevent considerable carbon emissions resulting from conversion of land that is not covered by the tax or a forest conservation scheme. In our scenarios this is predominantly the case for other land in PAS. Its special role emerges from its high productivity and its high carbon content. Based on data from Erb *et al* 2007 and FAO 2013 it was accounted 'other land' (cf supplementary material 3.1). Its high carbon content, however, would also justify including it in the forest pool, which would protect it from conversion and thus reduce land-use emissions and alter the supply of bioenergy.

Increased N_2O emissions are another adverse effect of bioenergy production reducing the GHG mitigation potential of bioenergy. They are of the same order of magnitude as the

CO_2 emissions due to bioenergy production. The tax clearly reduces total and bioenergy N_2O emissions. The bioenergy emissions comprise emissions from bioenergy production itself (direct) and increased emissions from agriculture resulting from intensification due to bioenergy production (indirect). With the finding that N_2O emissions might become a major part of the GHG balance of lignocellulosic biofuels, this study is in line with findings by Melillo *et al* (2009) and Popp *et al* (2011b). However, the latter study argues that the substantial negative emissions that could potentially be generated from biomass can overcompensate bioenergy N_2O emissions.

The energy yields of bioenergy presented in this study (200 GJ ha^{-1} yr^{-1} in 2005, around 600 EJ ha^{-1} yr^{-1} in 2055, and up to 700 GJ ha^{-1} yr^{-1} in 2095) are at the upper end of the range (130–600 GJ ha^{-1} yr^{-1}) reported by Haberl *et al* (2010) for 2055. This partly results from the fact that the model in our study predominantly chooses to produce biomass from herbaceous bioenergy crops (such as *Miscanthus*), which tend to feature higher yields than woody bioenergy crops (Fischer *et al* 2005) used in studies presented by Haberl *et al* (2010). Second, and in contrast to existing studies, bioenergy crop production in the present study competes for cropland with food crop production and thus bio-energy can be grown on highly productive land. Furthermore, the observed prices and underlying production patterns of bioenergy and food crops are based on decisive preconditions in the land-use model, i.e. (i) optimal global allocation of bioenergy and food production and (ii) optimal and timely investments into research and development (R&D) and full impact of R&D on all crops within a region. These optimal conditions are difficult to achieve in the real-world production system, exhibiting underinvestment into research and development (Alston *et al* 2009), consisting of numerous individual farmers who do not have equal access to technology, and facing land degradation, pests, and changes in weather and climate.

However, the high bioenergy yields at the end of the century are predominantly the result of yield increasing technological progress over almost 90 years. A large part of the yield increases in MAgPIE fills the yield gap between actual yields (observed land-use intensity in the starting year 1995) and the potential yields (derived from the vegetation model LPJmL) that can be achieved under best currently available management conditions. This yield gap can be substantial. For instance, in the regions with the highest yield increases, AFR, LAM, and PAS, the potential yields are reduced to obtain actual yields in 1995 by about 70, 50, and 60% respectively (supplementary material figure S12). MAgPIE bioenergy yields can exceed LPJmL bioenergy yields over time as endogenous investments in R&D push the technology frontier. For AFR, LAM, and PAS the yields in 2095 exceed the potential yields of 1995 by 80, 40, and 20% respectively. Since this study considers endogenous technological change, there is a response in yield growth to the pressure of bioenergy demand and forest conservation. This allows identification of the need for yield growth that would be required if a potential climate change mitigation policy demanded large-scale production of biomass accompanied by GHG prices. Therefore, the development of yields should be interpreted as projections of required yields rather than predictions of expected yields. To what extent they are realistic is currently under discussion. The performance of R&D for second-generation bioenergy crops is highly uncertain. Due to a lack of experience, there are no data available which could be used as a point of reference. Our assumption that yield increases for bioenergy crops will follow yield increases of food crops could be either optimistic or pessimistic. It could be optimistic, since for food crops mainly the corn:shoot ratio was improved and not the overall biomass production (as is required for second-generation bioenergy crops), or it could be pessimistic, since research on lignocellulosic bioenergy crops starts from zero, making it conceivable to assume that there should be a lot of ‘low hanging fruits’. Several studies doubt that such high yields could be achieved and argue that the natural productivity poses an upper bound to the production of bioenergy (Haberl *et al* 2013, Smith *et al* 2012, Field *et al* 2008, Erb *et al* 2012, Campbell *et al* 2008). Others argue that transferring bioenergy yield levels that were observed under test conditions to huge areas might overestimate the bioenergy potential (Johnston *et al* 2009). There are also concerns that raising energy crop yields beyond the natural productivity over large regions and over a long time, if possible at all, comes at the costs of increased GHG emissions and other adverse environmental impacts. The findings about bioenergy GHG emissions in the present study (see above) confirm the former at least. There is also doubt that even without bioenergy demand current yield trends will be sufficient to meet the food demand projected for 2050 (Ray *et al* 2013). On the other hand, Mueller *et al* (2012) indicate that substantial production increases (up to 70%) are possible by closing the yield gap with currently available management practices.

The following policy relevant conclusions can be drawn from the results. First, a potential climate policy that prices land-use and land-use change emissions could significantly increase supply prices of bioenergy, since it reduces the land available for bioenergy production and since it adds cost for fertilizer emissions to the production costs. Second, a carbon tax can be an effective measure to protect forests (or any other carbon stock under taxation), even if accompanied by large-scale bioenergy production. However, it can only protect land that is defined to be under emission control. The political question of which land to put under carbon taxation defines how much land is accessible. Thus, it is highly relevant not only for the effectiveness of nature conservation and emission mitigation but also for the supply of bioenergy. Third, the combination of the carbon tax *and* the bioenergy demand is expected to cause substantial pressure and strong intensification on the remaining land, particularly if biomass is produced at large scale. Energy crop yields would be required to rise beyond today’s potential yields. A climate policy that builds on carbon taxation and bioenergy deployment thus requires considerable accompanying R&D efforts that ensure continuous technological progress in the agricultural sector.

In this study, we investigated the impact of GHG prices on bioenergy supply. However, there are further crucial factors interacting with the long-term bioenergy supply that could be studied, such as food demand, different levels of forest and biodiversity protection, other land-use based mitigation options (e.g. afforestation), and bioenergy yields. The latter are particularly uncertain, since there is almost no practical experience with large-scale dedicated production of lignocellulosic biomass. Second, due to the potential competition with food production, the impact of bioenergy demand and GHG prices on food supply needs further research. Finally, the issue of fragmented climate policies leading to regionally non-uniform GHG prices and potential emission leakage needs to be considered for the environmental performance of bio-energy production.

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Supporting Online Material for the manuscript submission

"The global economic long-term potential of modern biomass in a climate constraint world"

1 Additional information on the MAgPIE model

1.1 Key characteristics of the MAgPIE model

Model feature	Implementation in MAgPIE	Source
Solution concept	Partial equilibrium, recursive dynamic, minimize total agricultural production costs	
Time horizon	1995-2095 in 10-year time steps	
Land available for food and feed production	Crop land, forest, other natural vegetation, other arable land	(Krause *et al* 2013)
Land available for bioenergy	The same as for food and feed crops	
Technological change (TC)	Endogenous	(Dietrich *et al* 2013)
Agricultural yields	Initial actual bioenergy yields in MAgPIE are derived from potential bioenergy yields in LPJmL by downscaling potential yields using information about observed land-use intensity (Dietrich *et al* 2012) and yields (FAO 2013). Actual yields in MAgPIE can increase due to endogenous TC. More	LPJmL (Bondeau *et al* 2007, Müller and Robertson 2013)

	information on agricultural yields can be found in (Humpenöder *et al* 2013)	
Water availability	The calculation of available water per grid cell is based on LPJmL	LPJmL (Bondeau *et al* 2007, Müller and Robertson 2013)
Water use efficiency	Irrigation efficiency is static	
Climate impacts	Not used in this study	
Food demand (Population, GDP)	SSP Database and SSP storylines	(O'Neil *et al* 2012, IIASA 2013)
Pasture	Static	
Forestry	Static	
Biodiversity protection	Forest protection, rainfed bioenergy only	(FAO and JRC 2012)
Area requirements for nature protection	Forest protection	(FAO and JRC 2012)
Trade/self-sufficiency and its variation	Endogenous trade but exogenous self-sufficiency	
Transport costs for bioenergy	Based on the GTAP 7 database (Narayanan and Walmsley 2008) and the transport distance to the next market (Nelson 2008)	
Irrigation of crops	Food crops: Rainfed and irrigated Bioenergy crops: Rainfed only	
Irrigation infrastructure	Starting point based on Siebert *et al* (2007). Can change endogenously.	
Land degradation	-	
GHG accounting	CO2, N2O, CH4 emissions	
Carbon pools that are considered	Vegetation, litter and soil carbon pool	
Carbon pools that are priced	Vegetation, litter and soil carbon pool of forest land	
Land use based mitigation	Marginal abatement cost curves (N2O, CH4)	(Lucas *et al* 2007)

1.2 MAgPIE regions

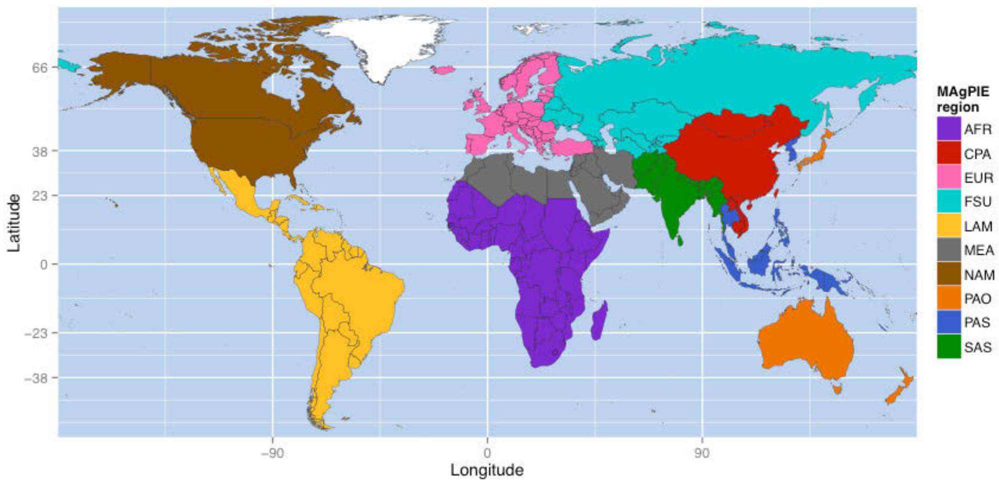


Figure S1: MAgPIE regions

MAgPIE	Region
AFR	Sub-Saharan Africa
CPA	Centrally planned Asia including China
EUR	Europe including Turkey
FSU	States of the former Soviet Union
LAM	Latin America
MEA	Middle East/North Africa
NAM	North America
PAO	Pacific OECD including Japan, Australia, New Zealand
PAS	Pacific (or Southeast) Asia
SAS	South Asia including India

Table S1: Names and abbreviations of the 10 economic world regions in MAgPIE.

2 Scenario design

2.1 Socio-economic assumptions

The socio-economic scenarios employed in this study are geared to the qualitative "Middle of the Road" narrative of Shared Socio-economic development Pathways (SSP) with intermediate socio-economic challenges for adaptation and mitigation (O'Neil *et al* 2012). Based on this SSP 2 narrative we assume a globalizing economy with medium rates of trade liberalization and medium rates of forest protection. Food, feed and material demand (c.f. Figure S2) is calculated using the methodology described in Bodirsky et al. (in review) based on the SSP 2 population and GDP projections (IIASA 2013). The SSPs do not incorporate climate policy by definition. For the purpose of this study we apply GHG taxes and bioenergy demand scenarios as exogenous parameters.

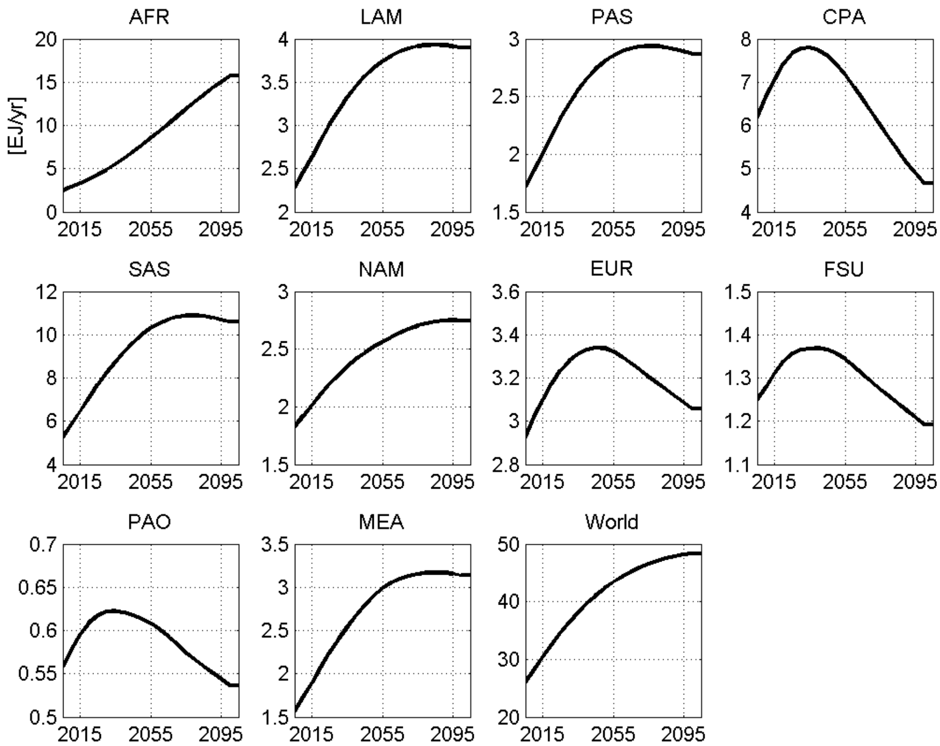


Figure S2: Global food demand scenario with regional breakdown.

2.2 Tax scenarios

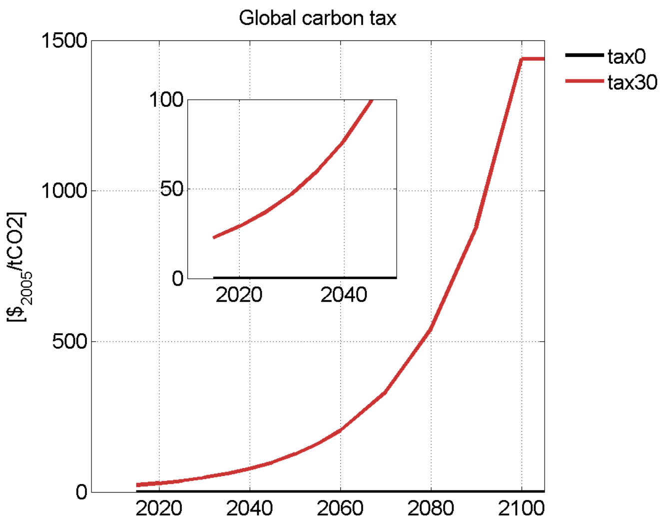


Figure S3: The two tax scenarios applied in this study. The tax30 scenario increases with 5 %/yr.

2.3 Deriving the supply price curves

The bioenergy supply price curves are derived by measuring the price response of the MAgPIE model to different global bioenergy demand scenarios. The demand scenarios and resulting price paths are available in 10-year time steps between 2005 and 2095. For each of the GHG tax scenarios the MAgPIE model was run with 73 different bioenergy demand scenarios. Each global bioenergy demand scenario yields a time path of regional allocation of bioenergy production and bioenergy price. Thus, in each time step and each region 73 combinations of bioenergy production and resulting bioenergy prices exist.

The regional supply curves were derived by fitting the function p(x,t,r) = a1(t,r) + a2(t,r) * x(t,r) ^ a3(r) using the method of least squares for p-p*, where p is the price calculated by the fit and p* the price calculated by MAgPIE. a1, a2, and a3 are the parameters to be adjusted, t is the time step, r the region and x the production of bioenergy (all fit coefficients are presented in the additional data-SOM).

The supply curves were derived using the full set of 73 demand scenarios. The scenarios start with a similar global demand of about 10 EJ in 2005 and evolve to values of 10 EJ to 270 EJ in 2055 and 50 EJ to 580 EJ in 2095. The sample scenario has a global demand of 145 EJ in 2055 and 240 in 2095. To identify the effect of bioenergy production we compare results of this sample scenario to a zero-demand scenario (see Figure S4).

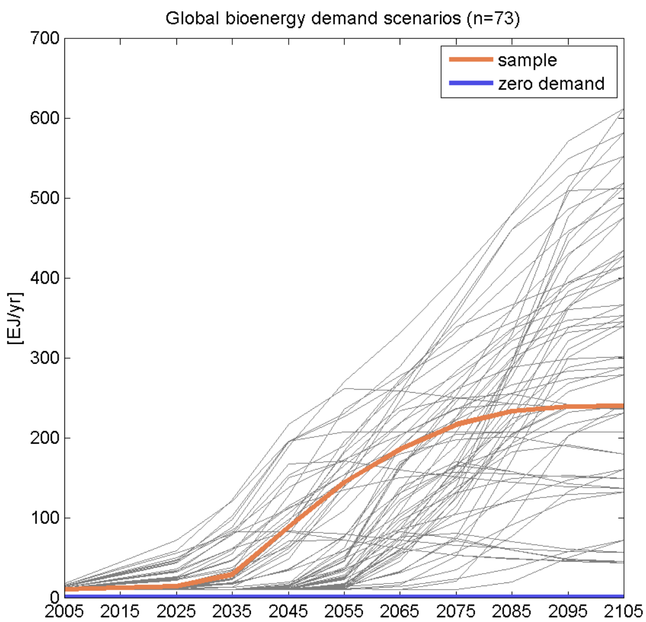


Figure S4: All bioenergy demand scenarios used for deriving the supply curves with the sample-scenario and the zero-demand scenario marked.

3 Additional results

3.1 Components of the effect of GHG taxes on the supply curves

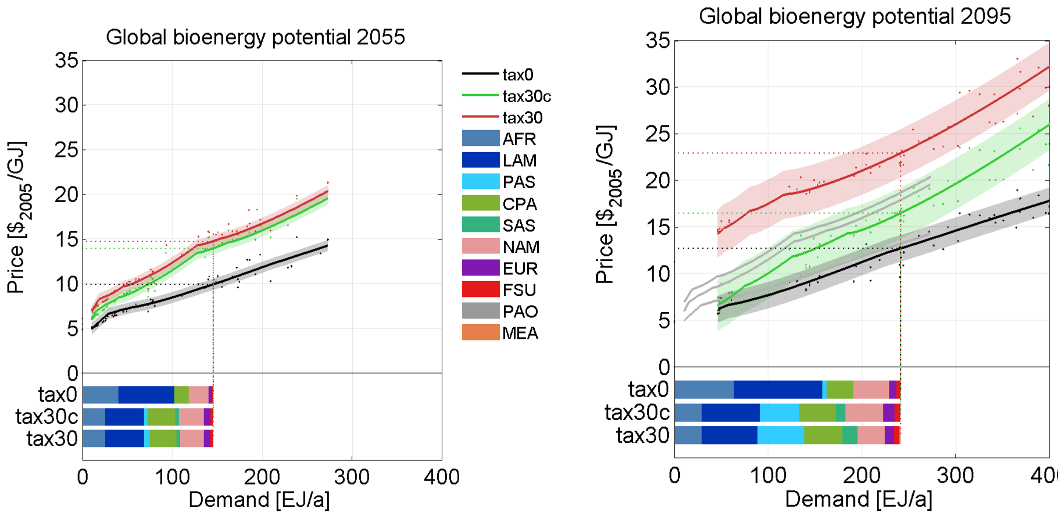


Figure S5: The different components of the price-elevating effect of GHG taxes: Globally aggregated bioenergy supply curves for the scenarios without the GHG tax (tax0), with a pure carbon tax (tax30c) and the GHG tax on all emissions (CO2,N2O, and CH4), (tax30).

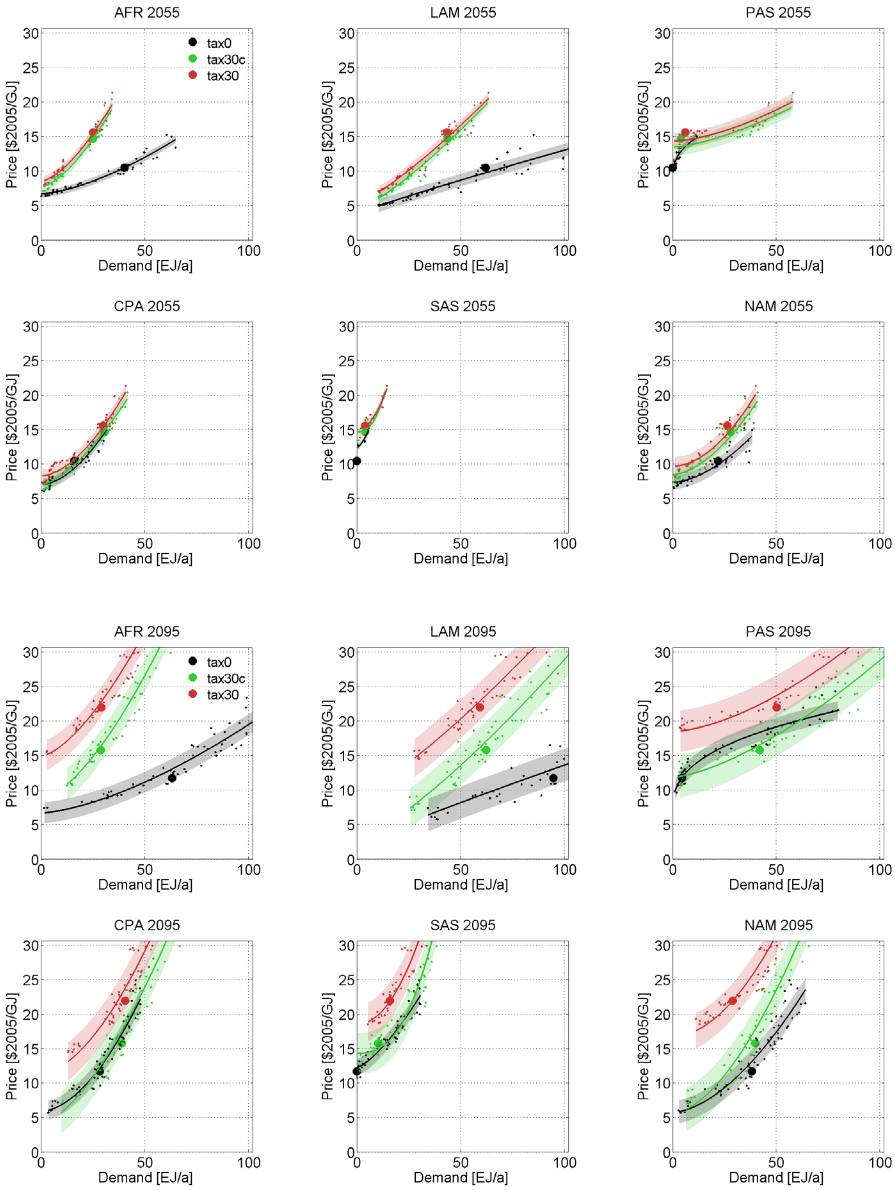


Figure S6: The different components of the price-elevating effect of GHG taxes: Regional bioenergy supply curves for the major bioenergy producers for the scenarios without the GHG tax (tax0, black), with a pure carbon tax (tax30c, green) and the GHG tax on all emissions, i.e. CO2,N2O, and CH4, (tax30, red).

On the special behavior of PAS: The supply curve of PAS changes its shape from the tax0 to the tax30 scenario. This is due to small amounts of forest that can be cleared in the tax0 scenario at low prices. This forest is protected by the tax in the tax30 scenario, letting the supply curve start at high prices for low demands already. High bioenergy demands in PAS are satisfied by expansion into other arable land both in the tax0 and the tax30 scenario, since resulting emissions are not included in the GHG tax. Thus PAS supply curves of the tax0 and tax30 scenarios share similar features at higher demands but differ for low demands. The low initial prices in the tax0 scenario lead to a fit of the data that is shaped concave. In the tax30 scenario the supply curve starts at higher prices and is convex. Other regions do not have access to *high productive* other land that can be used without being penalized by the GHG tax. Thus their supply curves are convex in all scenarios.

The high productive land in PAS with, at the same time, high carbon content was accounted "other arable land" in our scenarios. This is based on data from Erb *et al* 2007, who accounted huge areas of "grazing land" in PAS, which in MAgPIE is included into the pasture land pool. Since the FAO reports less grazing land in PAS, the difference between both sources was accounted "other arable land" in the MAgPIE scenarios used in this study and only the intersection was defined as pasture land.

3.2 Land allocation

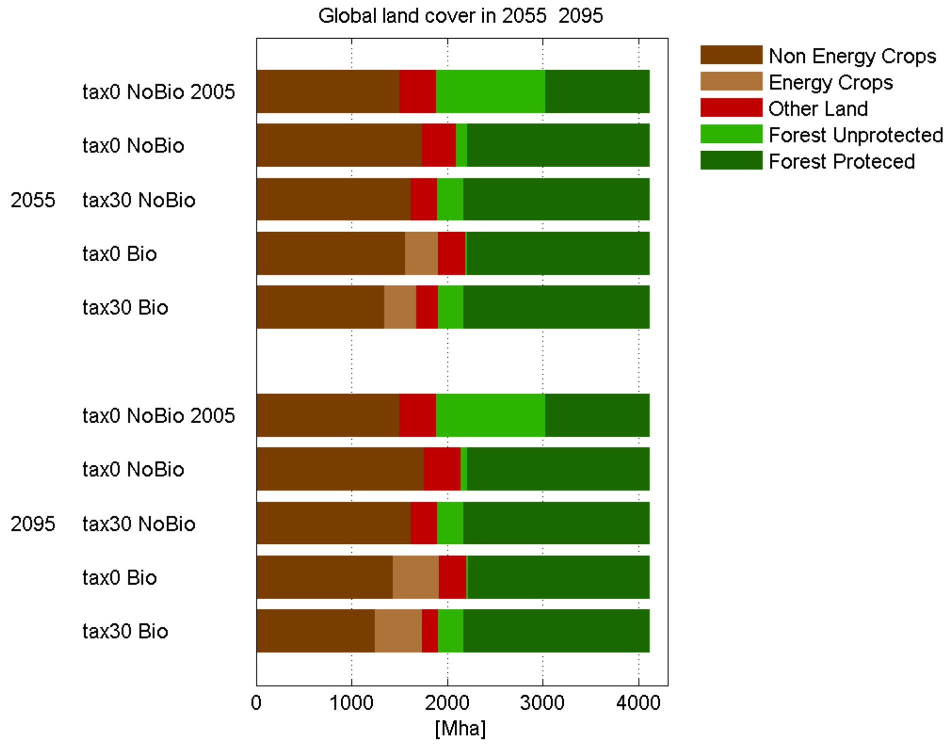


Figure S7: Global land cover in 2055 and 2095 for the four land types that are subject to the optimization and the four scenarios and the initial value in 2005.

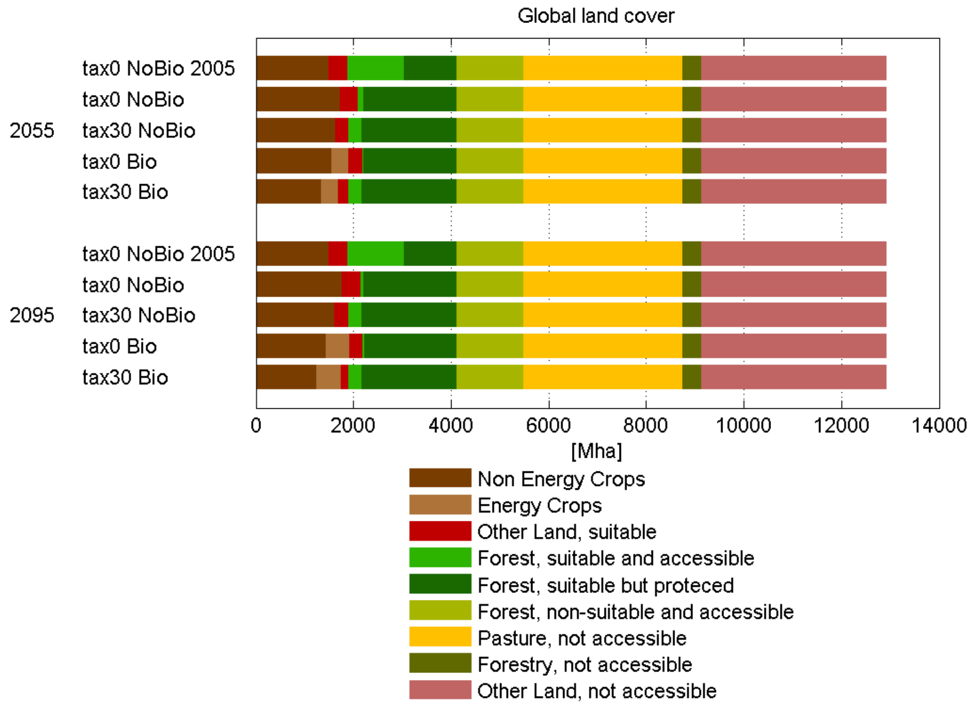
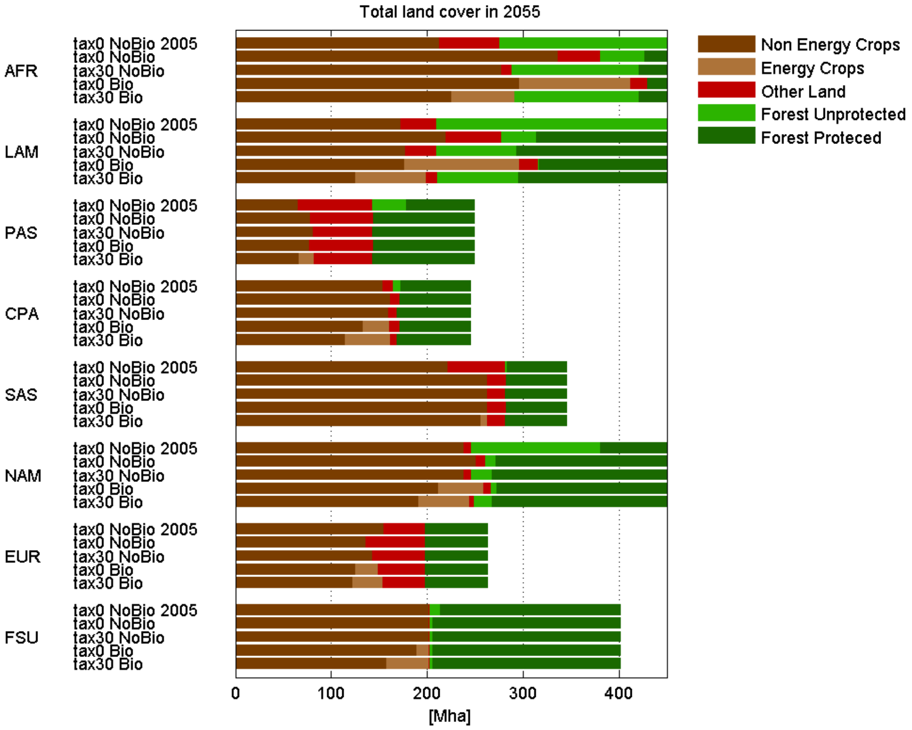


Figure S8: Global land cover in 2055 (top) and 2095 (bottom) for all land types and the four scenarios and the initial value in 2005.


Total land cover in 2055
AFR
LAM
PAS
CPA
SAS
NAM
EUR
FSU
tax0 NoBio 2005
tax0 NoBio
tax30 NoBio
tax0 Bio
tax30 Bio
0
100
200
300
400
[Mha]
Non Energy Crops
Energy Crops
Other Land
Forest Unprotected
Forest Proteced

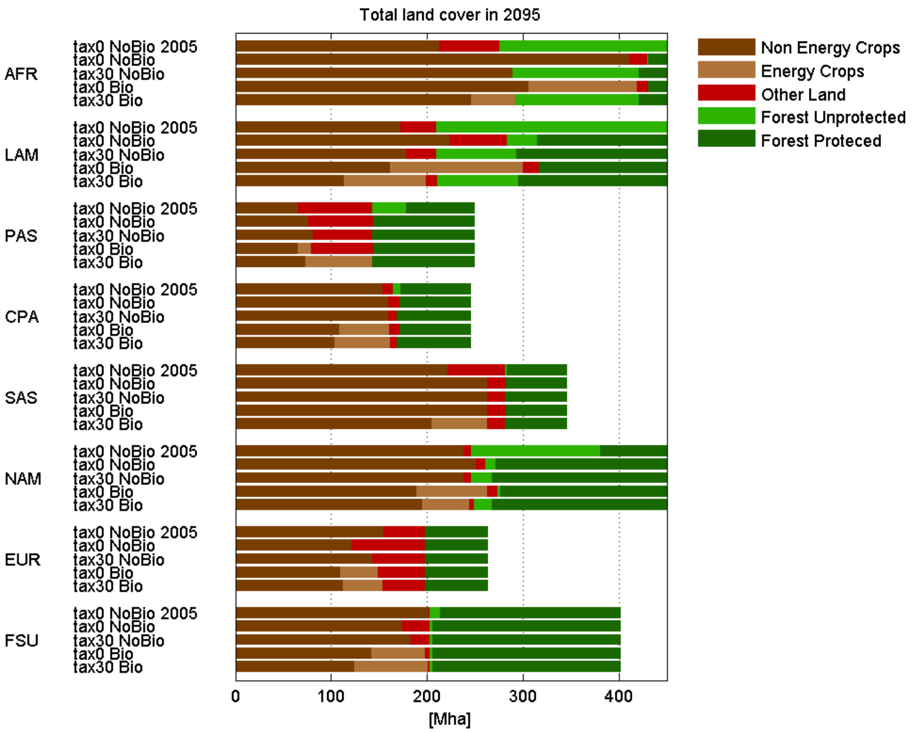

Total land cover in 2095
AFR
LAM
PAS
CPA
SAS
NAM
EUR
FSU
tax0 NoBio 2005
tax0 NoBio
tax30 NoBio
tax0 Bio
tax30 Bio
0
100
200
300
400
[Mha]
Non Energy Crops
Energy Crops
Other Land
Forest Unprotected
Forest Proteced

Figure S9: Regional land cover in 2055 (top) and 2095 (bottom) for the four land types that are subject to the optimization (and additionally for protected forest) for the four scenarios and the initial value in 2005. The figure focusses on the relevant range, thus AFR, LAM, and NAM are cut at 450 Mha.

3.3 Carbon emissions

The carbon tax pushes the carbon emissions backwards in time, since early deforestation is stopped by the tax and the land conversion in PAS (which causes CO_2 emissions) starts after 2050 when the pressure from bioenergy and food demand increases.

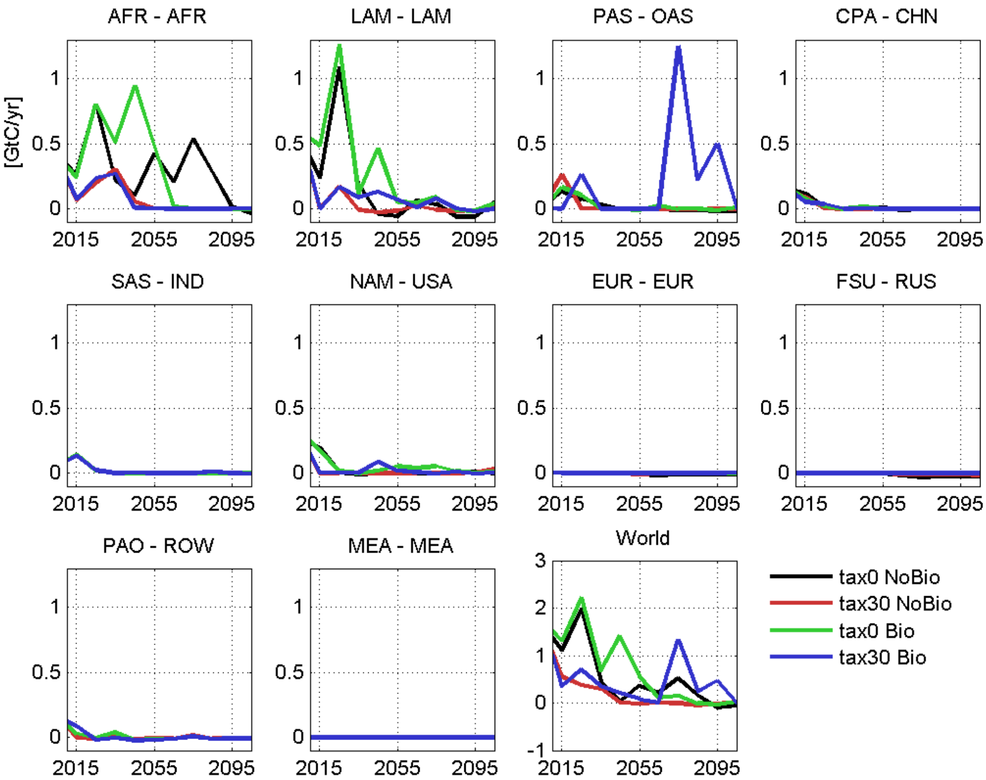


Figure S10: Total (agriculture + bioenergy) CO2 emissions over time for the four scenarios.

3.4 N_2O emissions

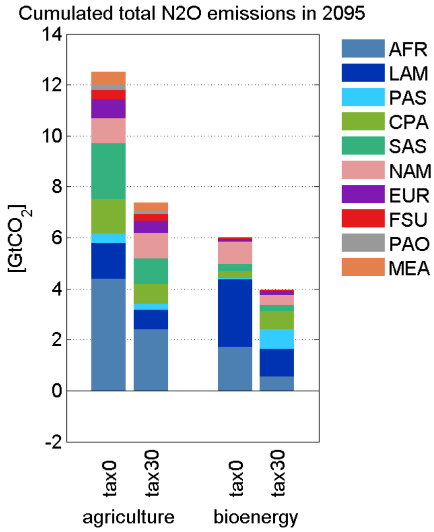


Figure S11: Total (agriculture + bioenergy) N2O emissions over time in GtCO2 equivalent for the four scenarios (CO2eq calculated with GWP100 of 298). The additional emissions due to bioenergy production comprise direct and indirect emissions, i.e. emissions from bioenergy production itself (direct) and increased emissions from agriculture resulting from intensification due to bioenergy production (indirect).

3.5 Bioenergy yields

Figure S12: Regional grassy bioenergy yields (rainfed only) from LPJmL (1995, green) and MAgPIE (1995, 2055, 2095, orange) from the sample scenario. LPJmL (Beringer et al 2011) represents potential yields, while MAgPIE aims to represents actual yields. Therefore, LPJmL yields are downscaled using information about observed land-use intensity (Dietrich et al 2012) and FAO yields (FAO 2013). It is assumed that LPJmL bioenergy yields represent yields achieved under highest currently observed land use intensification, which is observed in EUR. Therefore, LPJmL bioenergy yields for all regions are downscaled proportional to the land use intensity in the given region. In addition, yields are calibrated at regional level to meet FAO yields in 1995, resulting in a further reduction of yields in all regions. Due to yield-increasing technological change (TC) MAgPIE yields can exceed LPJmL yields until 2095.

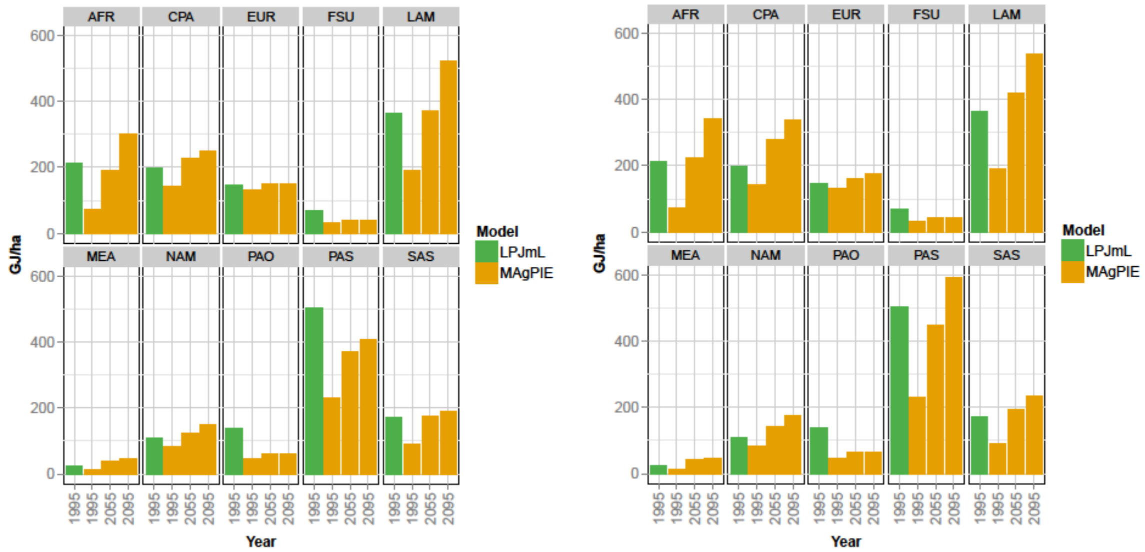


Figure S12: Bioenergy yields across regions for the scenarios without (left) and with GHG tax (right).

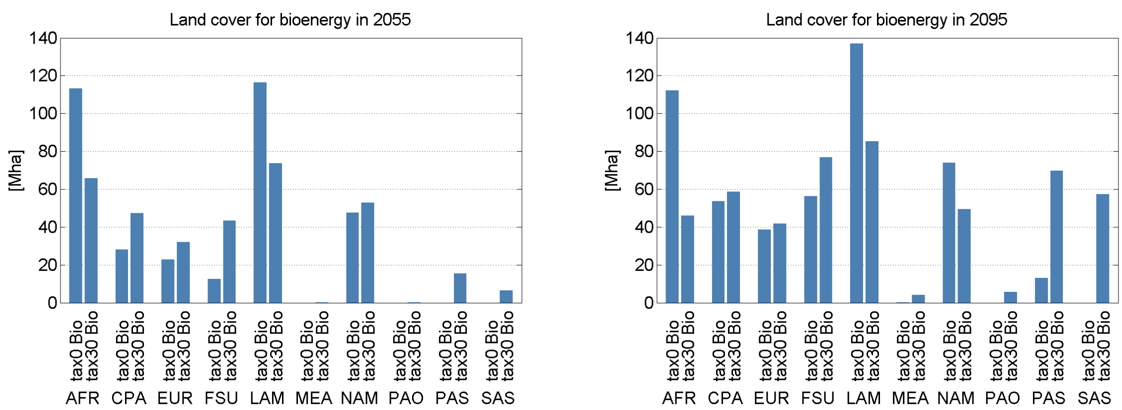


Figure S13: Bioenergy land cover across regions for the scenarios with and without GHG tax in 2055 and 2095

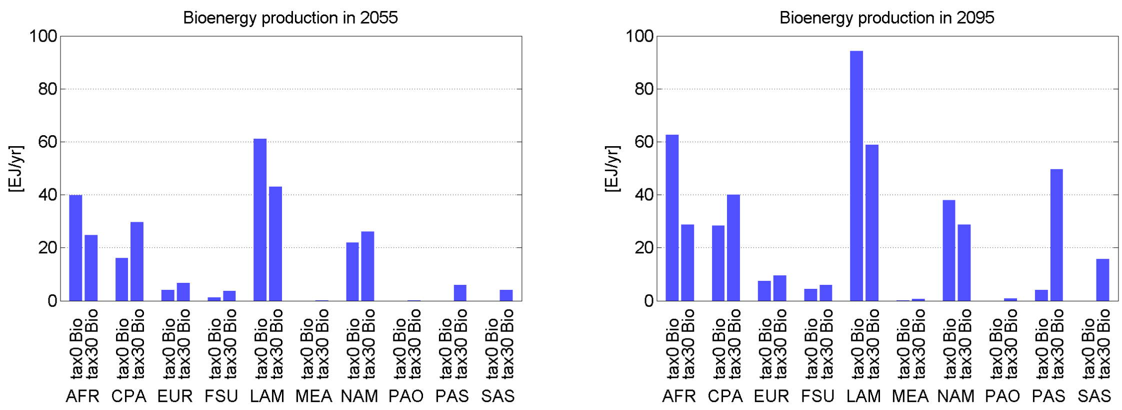


Figure S14: Bioenergy production across regions for the scenarios with and without GHG tax in 2055 and 2095

3.6 Agricultural yields

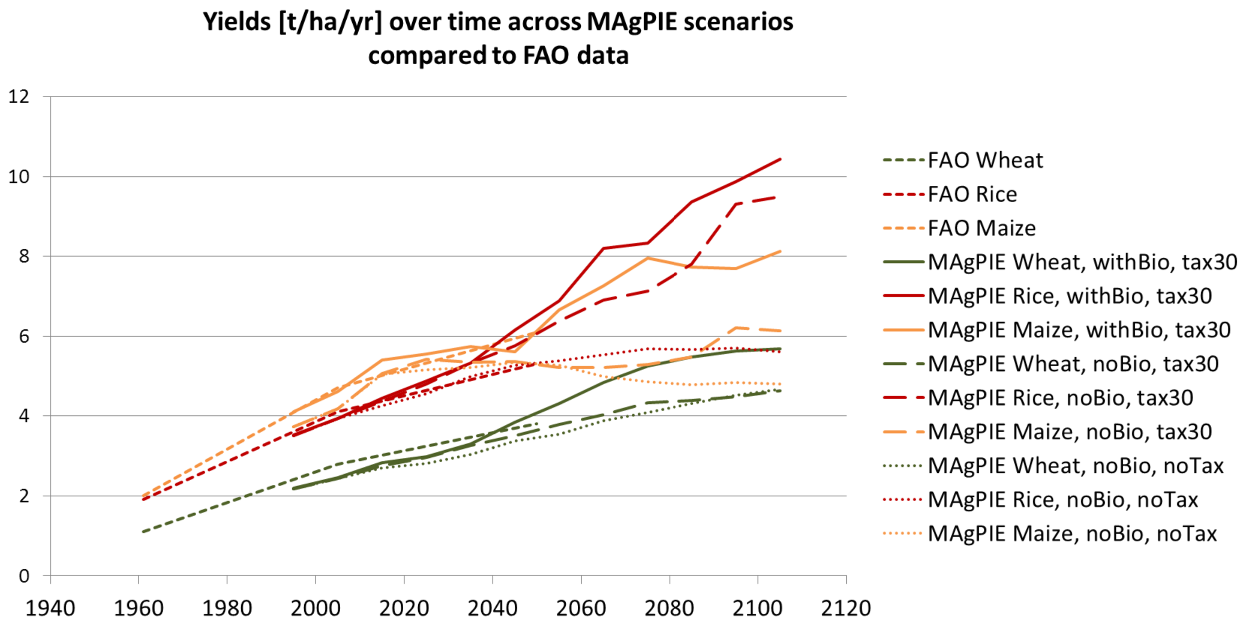


Figure S15: yields in t/ha/yr (dry mass) over time for maize, rice, and wheat from FAO data (Alexandratos and Bruinsma 2012, Table 4.12) and across three MAgPIE scenarios, i.e. without GHG tax and without bioenergy demand (noBio tax0); with GHG tax and without bioenergy demand (noBio, tax30); with GHG and with bioenergy demand (withBio, tax30).

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IV Trade-offs between land and water requirements for large-scale bioenergy production*

Authors:
Markus Bonsch, Florian Humpenöder, Alexander Popp, Benjamin Leon Bodirsky, Jan Philipp Dietrich, Susanne Rolinski, Anne Biewald, Hermann Lotze-Campen, Isabelle Weindl, Dieter Gerten and Miodrag Stevanovic

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GLOBAL CHANGE BIOLOGY BIOENERGY

GCB Bioenergy (2014), doi: 10.1111/gcbb.12226

Trade-offs between land and water requirements for large-scale bioenergy production

MARKUS BONSCH[1,2], FLORIAN HUMPENÖDER[1,2], ALEXANDER POPP[1], BENJAMIN BODIRSKY[1,2], JAN PHILIPP DIETRICH[1], SUSANNE ROLINSKI[1], ANNE BIEWALD[1], HERMANN LOTZE-CAMPEN[1,3], ISABELLE WEINDL[1,3], DIETER GERTEN[1] and MIODRAG STEVANOVIC[1,2]

[1]*Potsdam Institute for Climate Impact Research (PIK), Telegraphenberg, Potsdam 14473, Germany,* [2]*Economics of Climate Change, Technical University Berlin, Strasse des 17. Juni 145, Berlin 10623, Germany,* [3]*Humboldt University of Berlin, Unter den Linden 6, Berlin 10099, Germany*

Abstract

Bioenergy is expected to play an important role in the future energy mix as it can substitute fossil fuels and contribute to climate change mitigation. However, large-scale bioenergy cultivation may put substantial pressure on land and water resources. While irrigated bioenergy production can reduce the pressure on land due to higher yields, associated irrigation water requirements may lead to degradation of freshwater ecosystems and to conflicts with other potential users. In this article, we investigate the trade-offs between land and water requirements of large-scale bioenergy production. To this end, we adopt an exogenous demand trajectory for bioenergy from dedicated energy crops, targeted at limiting greenhouse gas emissions in the energy sector to 1100 Gt carbon dioxide equivalent until 2095. We then use the spatially explicit global land- and water-use allocation model MAgPIE to project the implications of this bioenergy target for global land and water resources. We find that producing 300 EJ yr^{-1} of bioenergy in 2095 from dedicated bioenergy crops is likely to double agricultural water withdrawals if no explicit water protection policies are implemented. Since current human water withdrawals are dominated by agriculture and already lead to ecosystem degradation and biodiversity loss, such a doubling will pose a severe threat to freshwater ecosystems. If irrigated bioenergy production is prohibited to prevent negative impacts of bioenergy cultivation on water resources, bioenergy land requirements for meeting a 300 EJ yr^{-1} bioenergy target increase substantially (+ 41%) – mainly at the expense of pasture areas and tropical forests. Thus, avoiding negative environmental impacts of large-scale bioenergy production will require policies that balance associated water and land requirements.

Keywords: bioenergy, land, land-use model, projection, sustainability, water, water-land nexus

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Introduction

A recent model intercomparison study projects bioenergy deployment between 70 and 230 Exajoules (EJ) per year in 2100 for scenarios without climate policy, with bioenergy primarily used to produce liquid fuels for the transport sector (Rose *et al*., 2014). With climate policies aiming at ambitious mitigation targets, bioenergy demand in 2100 is projected to reach 200–320 EJ yr^{-1} (Rose *et al*., 2014) since bioenergy in combination with carbon capture and storage can remove carbon dioxide from the atmosphere (Azar *et al*., 2006).

This bioenergy demand is in the same order of magnitude as the gross energy value of all harvested biomass in the year 2000 of around 300 EJ (Haberl *et al*., 2007). Therefore, concerns about negative environmental and societal implications of large-scale bioenergy production are discussed. It is expected that bioenergy production may require up to 550 Mha of additional cropland (Popp *et al*., 2014), corresponding to around 35% of current total cropland (FAO, 2013). Such substantial land requirements may have negative impacts on greenhouse gas emissions (Searchinger *et al*., 2008; Popp *et al*., 2011a, 2012), food prices (Lotze-Campen *et al*., 2014) and biodiversity (Smith *et al*., 2013).

Land requirements for bioenergy production are highly dependent on the achievable yield. Cultivation of dedicated bioenergy crops is very water intensive (Berndes, 2002; Gerbens-Leenes *et al*., 2009), so water limitations are a key constraint for achievable bioenergy yields in rainfed production systems. Reducing the water deficit by applying additional irrigation water plays a crucial role in achieving high yields (Smith *et al*.,

Correspondence: Markus Bonsch, tel. +49 331 288 2677, fax +49 331 288 2600, e-mail: bonsch@pik-potsdam.de

2012). Beringer *et al.* (2011) estimate that irrigation has the potential to increase bioenergy yields by more than 100% compared to rainfed production systems in large parts of India, Africa, Latin America, North America, and Australia. Irrigation may therefore be an option to reduce the pressure of bioenergy production on land resources.

Additional irrigation water requirements can however fundamentally change the global water cycle and put additional pressure on water resources. Potential water requirements of large-scale irrigated bioenergy production may be in the same order of magnitude as current total agricultural water withdrawals (Berndes, 2002; Beringer *et al.*, 2011) or even up to twice as high (Chaturvedi *et al.*, 2013). This is critical as many regions already face water scarcity (Falkenmark & Molden, 2008; Arnell *et al.*, 2011) and freshwater ecosystems are degraded by human activity (Poff & Zimmerman, 2010; Grafton *et al.*, 2012). We may thus face a fundamental trade-off between global land and water requirements for bioenergy production. A quantitative assessment of this trade-off is however lacking to date.

We investigate the land- and water-use implications of bioenergy production under two different scenarios using the spatially explicit land- and water-use allocation model MAgPIE (Model of Agricultural Production and its Impacts on the Environment) (Lotze-Campen *et al.*, 2008; Popp *et al.*, 2010). In the first scenario, no restrictions on irrigated bioenergy production are imposed. The share and spatial allocation of irrigated bioenergy production is determined endogenously based on economic optimization. The second scenario includes a policy that prohibits irrigated bioenergy cultivation. This setup allows us to quantify the implications of water-saving bioenergy production strategies for global land-use dynamics and natural land ecosystems.

Materials and methods

MAgPIE model

General description. Model of Agricultural Production and its Impacts on the Environment is a spatially explicit, global land- and water-use allocation model and simulates land-use dynamics in 10-year time steps until 2095 using recursive dynamic optimization (Lotze-Campen *et al.*, 2008; Popp *et al.*, 2010). The objective function of MAgPIE is the fulfilment of food, feed and material demand at minimum costs under socio-economic and biophysical constraints. Demand trajectories are based on exogenous future population and income projections (see Section Scenarios). Major cost types in MAgPIE are: factor requirement costs (capital, labour and chemicals, e.g., fertilizer), land conversion costs, transportation costs to the closest market and investment costs for technological change. Socio-economic constraints like demand, factor requirement costs and investment costs are defined at the regional level (10 world regions) (Figure S1). Biophysical constraints such as crop yields, carbon density, and water availability – derived from the global hydrology and vegetation model LPJmL (Bondeau *et al.*, 2007; Rost *et al.*, 2008; Müller & Robertson, 2014) – as well as land availability (Krause *et al.*, 2013), are introduced at the grid cell level (0.5 degree longitude/latitude; 59 199 grid cells). Due to computational constraints, all model inputs at 0.5 degree resolution are aggregated to 1000 simulation units for the optimization process based on a k-means clustering algorithm (Dietrich *et al.*, 2013). The clustering algorithm combines grid cells to simulation units based on the similarity of biophysical conditions.

MAgPIE features land-use competition based on cost-effectiveness at simulation unit level among the land-use related activities crop, livestock, and bioenergy production. Available land types are cropland, pasture, forest, other land (including nonforest natural vegetation, abandoned agricultural land and desert) and settlements. Cropland (rainfed and irrigated), pasture, forest, and other land are endogenously determined, while settlement areas are assumed to be constant over time. The forestry sector, in contrast to the crop and livestock sectors, is currently not implemented dynamically in MAgPIE. Therefore, timberland needed for wood production – consisting of forest plantations and modified natural forest – is excluded from the optimization (about 30% of the initial global forest area of 4235 Mha). In addition, other parts of forestland, mainly undisturbed natural forest, are within protected forest areas, which cover about 12.5% of the initial global forest area (FAO, 2010). Altogether, about 86% of the world's land surface is freely available in the optimization of the initial time-step.

Crop yields depend not only on biophysical conditions but also on management practices that differ across world regions and can change over time (Dietrich *et al.*, 2012). Therefore, biophysical yield potentials from LPJmL are calibrated to FAO yields (FAO, 2013) in 1995 before they enter MAgPIE. Regional land-use intensities that reflect the status of agricultural management in 1995 are derived from historical data (Dietrich *et al.*, 2012). MAgPIE can endogenously decide to invest into technological change (TC) on a regional level in order to increase land-use intensities, thereby increasing agricultural yields (Dietrich *et al.*, 2014). The ratio of TC investments to yield improvements (investment-yield ratio) is determined from historical data on agricultural Research and Development spending (Pardey *et al.*, 2006), agricultural infrastructure investments (Narayanan & Walmsley, 2008), and yields (FAO, 2013). The investment-yield ratio increases with the land-use intensity (Dietrich *et al.*, 2014), reflecting the fact that low land-use intensities can be improved by closing yield gaps while yield increases in intensive systems require higher investments to push the technology frontier.

The cost minimization problem is solved through endogenous variation in spatial rainfed and irrigated production patterns (subject to regional trade constraints; Schmitz *et al.*, 2012), land conversion (all at simulation unit level) and technological change (at regional level) (Lotze-Campen *et al.*, 2010).

Bioenergy. Present day modern bioenergy for electricity and liquid fuel generation relies mainly on conventional food crops such as maize and sugarcane (first generation bioenergy) (Gerbens-Leenes *et al*., 2009). To avoid competition with food production, techniques are being developed to convert the lignocellulosic components of plant biomass to biofuels (Schmer *et al*., 2008; Gerbens-Leenes *et al*., 2009). This will allow the use of dedicated grassy and woody bioenergy crops (second generation bioenergy) and is expected to increase the energy yield per unit of crop significantly (Gerbens-Leenes *et al*., 2009).

In MAgPIE, bioenergy feedstock consists of dedicated herbaceous and woody lignocellulosic bioenergy crops. Bioenergy demand enters the model as an exogenous trajectory at the global level (see Section Scenarios). Spatial allocation of bioenergy production is an endogenous model decision resulting from the cost minimizing objective function, which takes into account land and water availability as well as bioenergy yields, production costs, and competing demand for food and material.

In MAgPIE, bioenergy crops can be grown in rainfed and irrigated production systems. Rainfed and irrigated bioenergy yields at simulation unit level for the initialization of MAgPIE are derived from LPJmL (Beringer *et al*., 2011). While LPJmL simulations supply data on potential yields, i.e., yields achievable under the best currently available management options, MAgPIE aims at representing actual yields, i.e., yields realizable under actual current management that differs regionally. Therefore, LPJmL bioenergy yields are calibrated on regional level based on FAO yield data (FAO, 2013) and the ratio of regional land-use intensities to the European intensity. This is done because LPJmL potential bioenergy yields are consistent with observations from well-managed test sites in Europe and the United States (Beringer *et al*., 2011) and management intensities in other world regions are generally lower (Dietrich *et al*., 2012). Low calibration factors for Sub-Saharan Africa (0.28) and Latin America (0.38) reflect large yield gaps with respect to best management practices (Table S1).

Highest rainfed herbaceous bioenergy yields occur in the South-Eastern US, China, Pacific Asia and Latin America (Figure S2, Table S1). Irrigation renders regions attractive for bioenergy production, where rainfed yields are strongly water limited (Beringer *et al*., 2011): India, Northern Africa, Southern US and Australia. Within MAgPIE, endogenous investments into yield increasing technological change (see General description) affect all crops equally, including bioenergy crops.

Water and irrigation

In MAgPIE, available water at simulation unit level for domestic, industrial, and agricultural use comprises renewable blue water resources only, i.e., precipitation that enters rivers, lakes, and aquifers (Rost *et al*., 2008). Input data for available water is obtained from LPJmL (details in the Supplementary Online Material). We assume that all renewable freshwater is available for human use, i.e., no water is reserved for environmental purposes. Domestic and industrial water demand enters the model as an exogenous scenario (Figure S3) based on WaterGAP simulations (Alcamo *et al*., 2003; Flörke *et al*., 2013). We assume that domestic and industrial water demand is fulfilled first, effectively limiting water availability for agricultural use (similar to Elliott *et al*., 2013). Within these limits of available water, agricultural water demand for irrigated food, feed, and bioenergy production as well as livestock feeding is determined endogenously based on cost-effectiveness. Spatially explicit per hectare irrigation water requirements for the 16 food crops and two bioenergy crops represented in MAgPIE are obtained from LPJmL (see Supplementary Online Material), while livestock water requirements are based on FAO data (FAOSTAT, 2005). Rainfed crop production relies on green water resources only, i.e., precipitation infiltrated into the soil, and does therefore not affect agricultural irrigation water demand.

Irrigated crop production is not only constrained by water availability but also requires irrigation infrastructure for water distribution and application. The initial pattern of area equipped for irrigation is taken from the AQUASTAT database (Siebert *et al*., 2006). During the optimization process, the model can endogenously deploy additional irrigation infrastructure (see Supplementary Online Material). Irrigation costs comprise investment costs for the deployment of additional irrigation infrastructure as well as annual costs for operation and maintenance of irrigation systems (see Supplementary Online Material). Yield increases through technological change enhance land as well as irrigation water productivity (see Section Scenarios).

Scenarios

Food, livestock, and material demand (Figure S4) is calculated using the methodology described in Bodirsky *et al.* (under review, 2012), as well as SSP 2 population and GDP projections (IIASA, 2013). SSP2 population and GDP projections belong to a 'Middle of the Road' scenario from the Shared Socio-economic Pathways (SSP) scenario family (O'Neill *et al*., 2013) that is being developed as the successor of the widely used Special Report on Emissions (SRES) scenarios from the Intergovernmental Panel on Climate Change (IPCC) (Intergovernmental Panel on Climate Change, 2000) for use in climate change research.

Global primary bioenergy demand is obtained from Popp *et al.* (2011b), a study with a coupled version of MAgPIE and the global energy-economy-climate model REMIND (Leimbach *et al*., 2010). Within this modelling framework, primary bioenergy from dedicated bioenergy crops is used for electricity production via BioCHP (biomass combined heat and power; conversion efficiency 43%) and BIGCC (biomass integrated coal gasification combined cycle; conversion efficiency 31–42%), and liquid fuel production (conversion efficiency 40%). Bioenergy demand is calculated under climate policies that limit greenhouse gas emissions in the energy sector to 1100Gt CO2 equivalent up to 2095 and accounts for 25% of total primary energy in 2095 (Popp *et al*., 2011b). Other renewables (wind, solar, hydropower) also contribute 25% to global primary energy. Demand for primary bioenergy from dedicated bioenergy crops starts at 7 EJ yr^{-1} in 2015, strongly increases in mid-century and reaches a level of ~ 300 EJ yr^{-1} in 2095 (Table 1).

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Table 1 Trajectory of global dedicated primary bioenergy demand (EJ yr^{-1}) from Popp *et al.* (2011b)

	2015	2025	2035	2045	2055	2065	2075	2085	2095
EJ yr^{-1}	7	6	12	38	109	225	301	310	307

We investigate two bioenergy production scenarios (Table 2). In BE, dedicated bioenergy cultivation is unrestricted, i.e., the model can endogenously decide to use rainfed and irrigated production systems for bioenergy crops. BE_RF represents a water protection policy, where only rainfed bioenergy cultivation is allowed. Since the focus of this analysis is on resource requirements of bioenergy production and not on climate change mitigation targets, we assume that no climate change policy (e.g., emission pricing) is implemented in the land-use sector. In our standard model implementation, yield increasing technological change increases both, land productivity (output per hectare – tons ha^{-1}) and irrigation water productivity (output per m^3 of irrigation water – tons m^{-3}). For this setup, we assume that per hectare irrigation water requirements (m^3 ha^{-1}) are constant. Thus, technological change enhances irrigation water productivity (tons m^{-3}) by increasing the yield (tons ha^{-1}). To test the stability of our results, we perform a sensitivity analysis with static irrigation water productivity (static WP). For this setup, we assume that the irrigation water demand per ton output (m^3 ton^{-1}) is constant so that yield increases from technological change increase per hectare irrigation water demand (m^3 ha^{-1}). In our standard model, we assume that bioenergy crops can profit from technological change in the same way as food crops. Krausmann *et al.* (2013) however estimate that almost half of the past yield increases were due to increasing the share of harvested biomass to total plant biomass. This is more difficult to achieve for second generation bioenergy crops since all aboveground biomass can be used for energy production. We therefore conduct a sensitivity analysis where we assume that the effect of yield increases from technological change on second generation bioenergy crops is reduced by 50% compared to conventional crops (low Yields).

Results

Bioenergy production

Irrigation plays a key role for bioenergy provision in the BE scenario (Fig. 1). In 2095, 58% of global bioenergy supply stems from irrigated production. The region with the highest share of irrigated bioenergy production is South Asia with an irrigation share of 95% in 2095. Further regions with high irrigation shares are North America (71% in 2095), Sub-Saharan Africa (73%) and Latin America (50%). These high irrigation shares are driven by large differences between irrigated and rainfed yields (Figure S2). China is the only region, where bioenergy is mostly produced in rainfed systems (90% in 2095). Spatial allocation of bioenergy production (Fig. 2) to different world regions is mainly driven by spatial differences in bioenergy yields and varies between the scenarios. In the BE scenario, Latin America is the dominant production region contributing 160 EJ yr^{-1} in 2095. Further important bioenergy production regions are South Asia (40 EJ yr^{-1} in 2095), North America (35 EJ yr^{-1}), Sub-Saharan Africa (30 EJ yr^{-1}), and China (CPA, 30 EJ yr^{-1}). The remaining five regions do not contribute significantly to global bioenergy production (together 8 EJ yr^{-1} in 2095).

In the BE_RF scenario, irrigation of bioenergy areas is prohibited and consequently all bioenergy feedstock is provided from rainfed agriculture. Bioenergy production in Latin America and North America is similar to the BE scenario (160 EJ yr^{-1} and 30 EJ yr^{-1} in 2095 respectively). In South Asia on the contrary, rainfed bioenergy production is not competitive due to low yields (Figure S2) and no bioenergy is produced in the BE_RF scenario. This necessitates additional bioenergy production in other regions compared to BE. Bioenergy production increases significantly in Africa with an additional 35 EJ yr^{-1} in 2095 compared to BE. In China, bioenergy production increases by 5 EJ yr^{-1} and the remaining five regions provide an additional 3 EJ yr^{-1} in 2095. Even though bioenergy yields are high in Pacific Asia (Table S1), no bioenergy is produced there because forest requirements for wood production and

Table 2 Scenario definitions. In the standard model, yield increases affect land and irrigation water productivity. In the sensitivity runs, irrigation water productivity is static (static WP) and bioenergy crop yield increases are reduced to 50% compared to conventional crops (low Yields). Bioenergy cultivation is unrestricted in BE but limited to rainfed production systems in BE_RF

	MAgPIE model	Productivity increases	Bioenergy cultivation
BE	Standard model	Land and water	Rainfed and irrigated
BE_RF			Rainfed only
BE_staticWP	Static WP	Land only	Rainfed and irrigated
BE_RF_staticWP			Rainfed-only
BE_lowYields	Low Yields	Land and water; 50% penalty on bioenergy crops	Rainfed and irrigated
BE_RF_lowYields			Rainfed-only

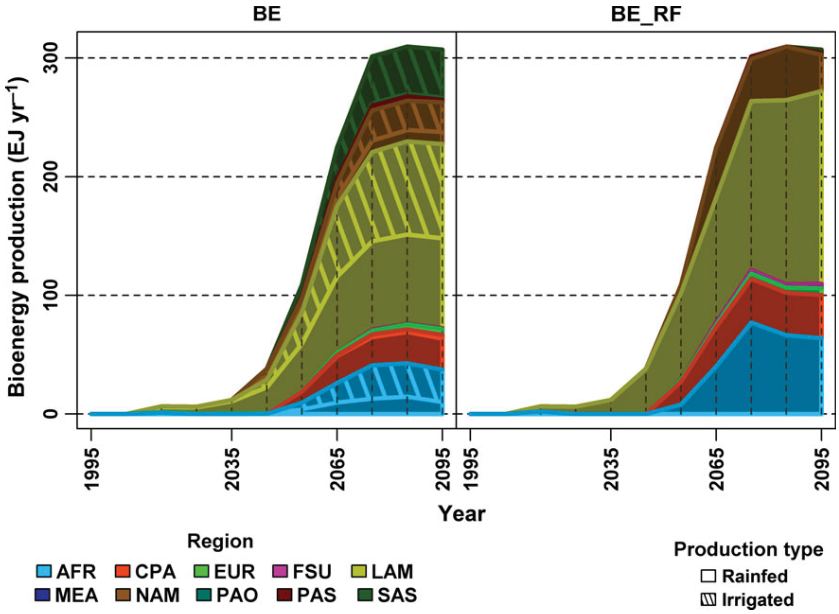

Fig. 1 Regional rainfed and irrigated bioenergy production for BE and BE_RF. AFR = Sub-Saharan Africa, CPA = centrally planned Asia including China, EUR = Europe, FSU = former Soviet Union, LAM = Latin America, MEA = Middle East and North Africa, NAM = North America, PAO = Pacific OECD, PAS = Pacific Asia, SAS = South Asia.

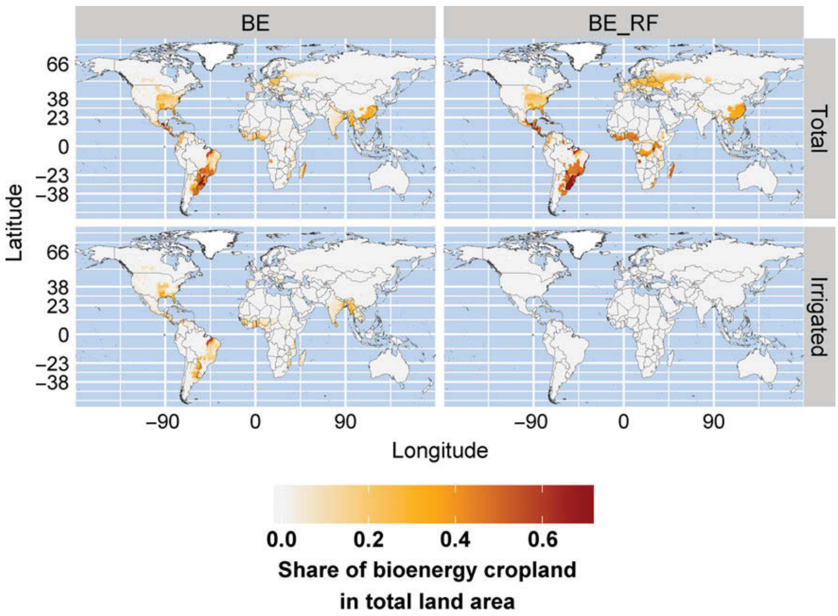

Fig. 2 Spatial allocation of bioenergy cropland for BE (left) and BE_RF (right). Colours indicate the share of bioenergy cropland in total land area. Top row: total bioenergy cropland. Bottom row: irrigated bioenergy cropland.

nature conservation limit land availability (see Section MAgPIE model).

Agricultural water withdrawals

Global agricultural water withdrawals (AWW) for the BE and BE_RF scenarios develop similarly until 2035 (Fig. 3) since almost no bioenergy is produced. Total AWW (energy crops + non-energy commodities) in 1995 are 2926 km^3 and increase to approximately 3250 km^3 in 2035 due to increasing food demand (Figure S4). The development of AWW in our projections in the near future is consistent with the historical trend (Shiklomanov, 2000), but in 1995 our estimate of AWW is around 400 km^3 higher than the one by Shiklomanov. Our initial value is however consistent with historical data around the year 2000 given the uncertainty range from different irrigated area patterns and climate datasets (2200–3800 km^3), (Wisser *et al.*, 2008).

Due to additional water withdrawals for bioenergy crops, the BE scenario exhibits a steep increase in total AWW after 2035, reaching 6400 km^3 in 2075 and levelling off afterwards. Water withdrawals for irrigated food and material crop production and livestock production (nonenergy commodities) in the BE scenario increase moderately until the mid of the century (3250 km^3 in 2055) due to increasing demand for nonenergy commodities. In the second half of the century, the strong increase in bioenergy demand (Figure S4) leads to increased competition for water. Furthermore, demand for nonenergy commodities stagnates while ongoing yield increases from technological change (Fig. 7) continue to increase irrigation water productivity (see section Scenarios). Irrigation water withdrawals for nonenergy commodities therefore decrease slightly in the second half of the century and amount to 3050 km^3 (48% of total withdrawals) in 2095.

Agricultural water withdrawals in the BE_RF scenario in contrast are solely driven by food and material production and increase more slowly until 2055 (3460 km^3). In BE_RF, bioenergy does not compete with other crops

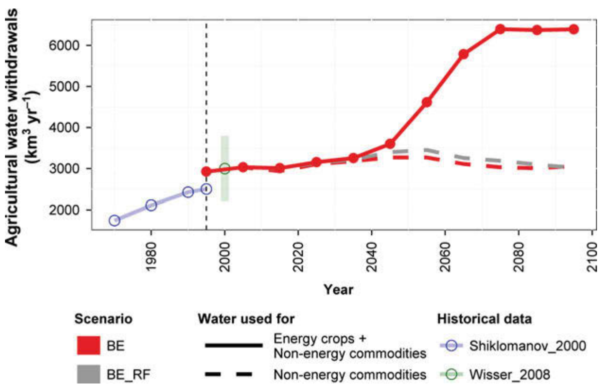

Fig. 3 Global agricultural water withdrawals for BE (rainfed and irrigated bioenergy production allowed) and BE_RF (only rainfed bioenergy production allowed). Total water withdrawals (energy crops + non-energy commodities) appear as a solid line for BE. Dashed lines depict water withdrawals for nonenergy commodities (irrigated food crops, livestock production, and irrigated material crops) only. In BE_RF, water withdrawals for nonenergy commodities equal total agricultural water withdrawals. Historical data from Shiklomanov (2000) and Wisser *et al.* (2008) is displayed for comparison. Wisser *et al.* provide an uncertainty range that is depicted as a shaded area. The vertical dashed line marks the start of the simulation period.

for water, but rainfed bioenergy production can replace irrigated non-energy crops. Therefore, the development of AWW in the second half of the century in BE_RF is similar to water withdrawals for nonbioenergy commodities in BE. The BE_RF scenario requires 53% less irrigation water in 2095 than the BE scenario.

Regional water withdrawals for bioenergy crops in the BE scenario are highest in Latin America, Africa, South Asia, and North America (Fig. 4). AWW for nonenergy commodities in Latin America, Africa, and North America are similar or even higher in BE than in BE_RF indicating that additional water resources are tapped for bioenergy production. In South Asia, bioenergy crops compete directly for water with nonenergy crops indicated by the reduction in AWW for nonenergy commodities in BE compared to BE_RF. This competition for water in South Asia leads to a slight decrease in global AWW for nonenergy commodities in BE compared to BE_RF (Fig. 3).

Land-use change

By the end of the century, bioenergy production will require substantial amounts of land (Fig. 5). In the BE scenario, dedicated bioenergy cropland reaches 490 Mha in 2095. Prohibiting irrigated bioenergy production increases this value by 200 Mha or 41% in the BE_RF scenario. Additional pressure from increasing food demand (Figure S4) drives expansion of cropland for food, feed, and material production (nonenergy cropland) that amounts to 200 Mha (BE) and 180 Mha (BE_RF) until 2095. Increasing bioenergy and nonenergy cropland requirements are fulfilled at the expense of natural forests and pasture. In the BE scenario, global forest and pasture areas decrease by 420 and 470 Mha respectively until 2095. Other land increases by 70 Mha until 2095 due to abandonment of agricultural land. Intensification in the livestock sector leads to reduced demand for animal feedstock from pasture and a reduction in pasture area. Since not all abandoned pasture area is suitable for cropping activities, this process is the main driver for the abandonment of agricultural land. Between 2075 and 2095, bioenergy demand and demand for nonenergy commodities stagnates (Figure S4) while continued technological improvements continue to increase agricultural yields (Fig. 7). Therefore, reductions in bioenergy cropland and nonenergy cropland further contribute to the increase in other land during this period.

The general pattern in the BE_RF scenario is similar to the BE scenario. Additional forest losses are 160 Mha and pasture decreases by an additional 140 Mha until 2095 (Fig. 5). On a regional level, additional forest losses in BE_RF compared to BE are highest in Africa (70 Mha in 2095), Latin America (50 Mha) and North America

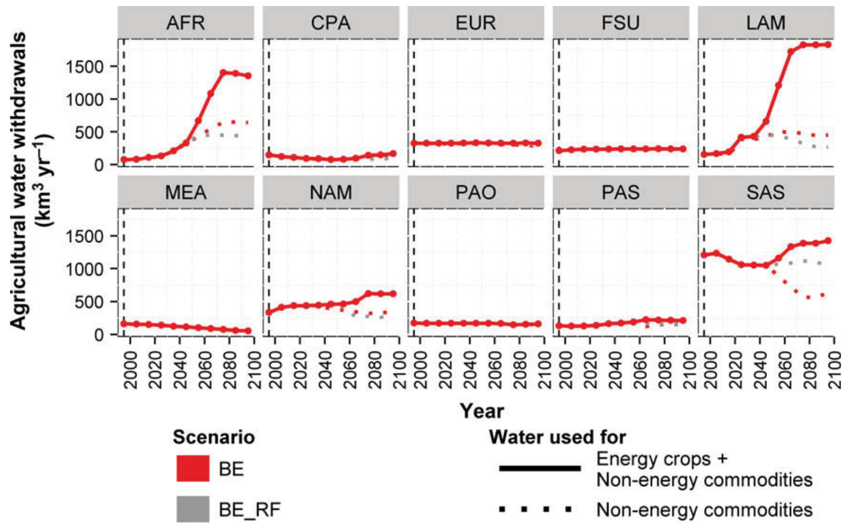

Fig. 4 Regional agricultural water withdrawals for BE and BE_RF. Total water withdrawals (Energy crops + non-energy commodities) appear as a solid line for BE. Dashed lines depict water withdrawals for nonenergy commodities (irrigated food crops, livestock production, and irrigated material crops) only. For BE_RF, irrigation of bioenergy crops is prohibited so that water withdrawals for nonenergy commodities equal total water agricultural withdrawals. The vertical dashed line marks the start of the simulation period.

(40 Mha) (Figure S5). In BE_RF, more land is abandoned between 2075 and 2095 than in BE due to stronger agricultural intensification at the end of the century.

Carbon dioxide emissions from land-use change (Figure S6) in BE_RF amount to 455 Gt CO2 between 1995 and 2095. Compared to emissions in BE of 316 Gt CO2 over the century, they are 44% higher because of increased agricultural land requirements and associated land-use change.

To test our results, we compare regional MAgPIE projections for cropland and pasture with FAO data (FAO, 2013) (Figures S7, S8). Deviations of regional MAgPIE cropland in 1995 from FAO data stay below 12% and deviations in regional pasture area are below 20%. The near term trend in the MAgPIE projections is in general similar to historical trends. The only exception is in the Middle-East and North Africa, where MAgPIE cropland and pasture are lower than FAO data by ~30%. The reason for this behavior is that MAgPIE prefers a more intensive production pathway in the Middle-East than observed in reality. Thus, early investments into technological change increase yields above real world levels and lead to reduced land requirements.

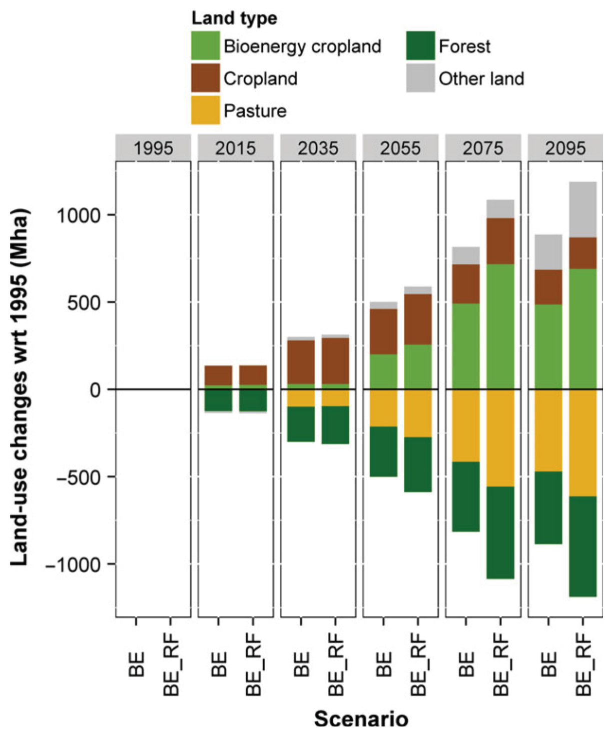

Fig. 5 Global land-use change over the century with respect to 1995 for BE and BE_RF for the land types represented in MAgPIE. Total cropland is split into bioenergy cropland and cropland for food, feed and material production (Cropland). Positive values indicate an increase, negative values a decrease in the corresponding land pool.

Bioenergy prices

Bioenergy supply prices as calculated by MAgPIE reflect the marginal costs of producing one additional unit of bioenergy given the current bioenergy demand.

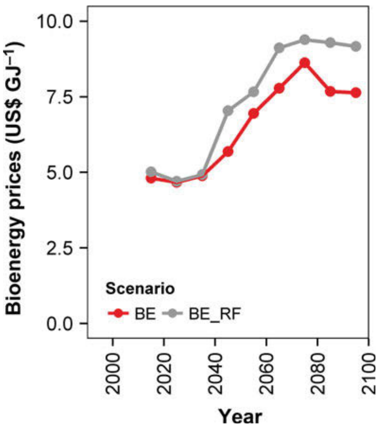

Fig. 6 Bioenergy prices for BE and BE_RF. Prior to 2015, no prices can be calculated since no bioenergy is produced.

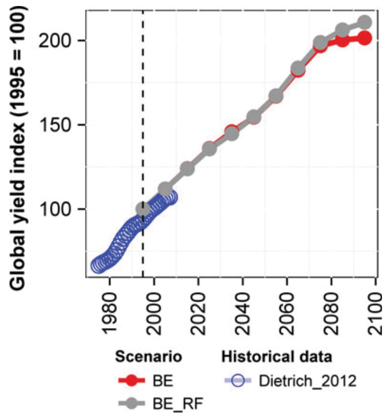

Fig. 7 Global yield index (1995 = 100) for BE and BE_RF. Changes reflect yield increases due to technological change on regional level. The global average is calculated using crop area as a weight. Historical data from Dietrich *et al.* (2012) are displayed for comparison. The vertical dashed line marks the start of the simulation period.

In the BE scenario, supply prices for primary energy from dedicated bioenergy crops increase from ~5 US $/GJ in 2015 to 8.6 US$/GJ in 2075 due to increasing bioenergy demand (Fig. 6). Afterwards, bioenergy supply prices slightly decline due to demand stagnation and reach 7.6 US$/GJ in 2095 for a production of ~300 EJ yr^{-1} of bioenergy. In BE_RF, bioenergy supply prices follow a similar trajectory and are always higher than in BE. In 2095 BE_RF exhibits a bioenergy price of 9.2 US $/GJ, around 20% higher than in BE.

Yield growth due to technological change

Yield growth for agricultural crops followed a linear trend in the past (Hafner, 2003; Fischer & Edmeades, 2010). The calculation of average annual growth rates would thus be misleading since it would suggest exponential growth. We therefore report yield growth due to technological change by calculating a global yield index (1995 = 100) (Fig. 7). Investments into yield increasing agricultural research and development are an endogenous model decision on regional level. Until 2075, increasing demand for agricultural products (Figure S4) leads to an approximately linear increase in global yield levels by ~12 points per decade. Afterwards, the yield trajectory flattens out, especially for BE, because demand stagnates and there is no further incentive for the model to invest into technological change. Regional yield increases (Table 3) are highest in the Middle East, Africa, Latin America, and South Asia. Initial land-use intensities in these regions are low and yield improvements can be achieved by closing yield gaps at low costs. In Europe and North America in contrast, initial land-use intensities are high. Further yield increases therefore require pushing the technology frontier, are expensive, and therefore less attractive. Historical data from Dietrich *et al.* (2012) shows global yield increases due to technological change by ~14 points per decade after 1960. Fischer & Edmeades (2010) find that yields for the important food crops maize, rice and wheat increased at about 8 to 16 points per decade between 1988 and 2007. Historical corn yield levels in the United States increased at ~14 points per decade between 1960 and present (Egli, 2008). Thus, our productivity pathway is compatible with historical data at the global scale. It is however unclear, whether historical yield trends can be maintained after current yield gaps have been closed (Cassman, 1999). In our projections, bioenergy yields stay within the yield potential achievable under current best management as simulated by LPJmL for most regions (Figure S9, left). In Latin America however, MAgPIE bioenergy yields at the end of the century exceed LPJmL potential yields by 12%.

Sensitivity analysis

In the standard implementation, yield gains from technological innovation increase land and irrigation water productivity simultaneously (see Section Scenarios). If technological change only increases land productivity and leaves irrigation water productivity unchanged (static WP), water withdrawals for BE and BE_RF are significantly higher than in the standard model (Table 4). The relative difference in AWW between BE and BE_RF in 2095 is however comparable for the standard model (110%) and the static WP model (100%).

Since water is less productive in static WP at the end of the century, less bioenergy area can be irrigated in the BE scenario for static WP. Therefore, static WP requires more total bioenergy area in the BE scenario than the standard model and forest losses until the end

Table 3 Regional yield index in 2095 for BE and BE_RF (1995 = 100). The global average is calculated using crop area as a weight

	WORLD	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
BE	201	317	167	110	109	267	409	146	113	150	239
BE_RF	211	331	167	110	108	295	409	152	111	148	219

Table 4 Results of the sensitivity analysis. The first row contains results for the standard model for the scenarios BE and BE_RF. The second row depicts results for a model version with no improvements in irrigation water productivity (static WP). The third row contains results for a model version where bioenergy crop yields increase at half the rate of conventional crops (low Yields). Per cent numbers indicate the difference between the sensitivity results and the corresponding standard model results

Model run	Agricultural water withdrawals 2095 (in km^3 yr^{-1})		Total bioenergy area in 2095 (in million ha)		Irrigated bioenergy area in 2095 (in million ha)		Forest lost between 1995 and 2095 (in million ha)	
Standard model								
BE	6393		486		228		416	
BE_RF	3031		689		0		576	
Static WP								
BE_staticWP	8879	+38%	568	+16%	142	–38%	516	+24%
BE_RF_staticWP	4456	+47%	683	−1%	0	+0%	560	−3%
Low Yields								
BE_lowYields	8306	+30%	740	+52%	350	+53%	556	+33%
BE_RF_lowYields	2446	−20%	1002	+45%	0	+0%	690	+20%

of the century are higher. Bioenergy area in the BE_RF scenario is not affected by different irrigation water productivity assumptions.

If yield increases from technological change are only half as efficient for bioenergy crops as for traditional crops (low Yields), bioenergy land requirements increase substantially and reach up to 1002 Mha for BE_RF. With lower yields, irrigation becomes even more attractive and AWW in BE increase by 30% compared to the standard model. In BE_RF, AWW are reduced because rainfed bioenergy cropland replaces irrigated food cropland. Bioenergy yields are lower in the low Yields model than in the standard model and stay within yield potentials as simulated by LPJmL (Figure S9, right).

To test the sensitivity of our results with respect to bioenergy demand, we conduct a sensitivity analysis where we reduce bioenergy demand in 15% steps from the original demand of 307 EJ yr^{-1} in 2095 (Figure S10). While for both scenarios, bioenergy area decreases with decreasing demand, bioenergy area in BE_RF is higher than in BE over the range of demand scenarios considered. For a demand reduction of 30%, BE_RF requires the same amount of bioenergy area as BE with the full demand of 307 EJ yr^{-1}.

Discussion

Several studies have highlighted that large-scale irrigated bioenergy production may require significant amounts of water and fundamentally alter the state of global freshwater resources (Berndes, 2002; Beringer *et al.*, 2011; Chaturvedi *et al.*, 2013). The present study investigates the trade-offs between water and land resources for producing ~300 EJ of bioenergy per year in 2095 from dedicated energy crops using a spatially explicit global land and water-use allocation model. We compare a scenario where irrigation water use for bioenergy production is allowed within the limits of available water (BE) to a rainfed-only bioenergy production scenario that aims at minimizing the impacts of bioenergy production on water resources (BE_RF). This experimental setup allows us to determine the water-use implications of large-scale bioenergy production as well as the land-use implications of water-saving bioenergy production strategies.

Implications of bioenergy production for water resources

Our results suggest that irrigation will play a key role in providing bioenergy feedstock if no policy restrictions are imposed. In contrast to comparable studies (Berndes, 2002; Chaturvedi *et al.*, 2013), the decision between rainfed and irrigated bioenergy production is treated here as an endogenous process. Thus, the large irrigated fraction in total bioenergy production (58%) in the BE scenario reflects comparative advantages, especially significant yield improvements through irrigation in important bioenergy production regions such as India, Latin America, North America, and Africa. This is in line with results by Beringer *et al.* (2011) who found that natural water limitations reduce bioenergy yields in large parts of these regions by up to 100% of the yield achievable without water limitations.

In this study, irrigation water requirements associated with the production of 300 EJ/yr of second generation bioenergy crops reach 3350 km^3 if no policy restrictions on irrigated bioenergy production are imposed. This number is comparable to current global agricultural water withdrawals (Shiklomanov, 2000; Wisser *et al.*, 2008) and is consistent with previous studies on bioenergy water withdrawals. Beringer *et al.* (2011) estimates irrigation water requirements of large-scale bioenergy production of 1500–3900 km^3. Chaturvedi *et al.* (2013) explore the water-use implications of several climate change mitigation scenarios. They project water withdrawals for bioenergy production between 670 and 5200 km^3 depending on the bioenergy deployment (<100–850 EJ yr^{-1}). Given the substantial associated water withdrawals, the question whether irrigated bioenergy production will impair freshwater ecosystems needs to be addressed. Experience from past and present human influence on water resources suggests that even current levels of human water withdrawals pose a major threat to aquatic ecosystems. It has been estimated that freshwater vertebrate populations have declined by 54% globally and that 32% of the world's amphibian species are threatened with extinction due to human interference (Dudgeon *et al.*, 2006). Hoekstra *et al.* (2012) have estimated that human water use exceeds the sustainably allowed level at least 1 month per year in 223 of 405 large river basins globally. A recent special issue has highlighted that direct human influence will pose the biggest threat to freshwater ecosystems in the coming decades (Vörösmarty *et al.*, 2013). Since agriculture contributes around 70% to current human water withdrawals (Rost *et al.*, 2008), these studies suggest that the projected doubling of agricultural water withdrawals due to large-scale bioenergy production will have substantial adverse impacts on freshwater ecosystems. Especially projected irrigated bioenergy production in South Asia (40 EJ yr^{-1}), a region facing severe water scarcity and overexploitation of groundwater resources (de Fraiture *et al.*, 2008; Biewald *et al.*, 2014) is worrisome in this context.

Implications of a water-saving bioenergy production strategy

Can ambitious bioenergy targets be reached without threatening global water resources? In our experimental setup, it is possible to produce 300 EJ yr^{-1} of bioenergy – an amount comparable to current total human appropriation of primary biomass production (Haberl *et al.*, 2007) – without tapping additional blue water resources for irrigation. There are, however, caveats associated with such a rainfed-only bioenergy production scenario.

Land requirements for producing ~300 EJ yr^{-1} of bioenergy increase significantly if irrigated bioenergy production is prohibited since rainfed bioenergy yields are lower than irrigated yields. In our simulations, an additional 200 Mha of bioenergy cropland will be required if irrigated bioenergy production is prohibited. This corresponds to the extent of current total cropland in the United States and Australia together (~210 Mha) (FAO, 2013). A recent model intercomparison exercise projects land requirements for the production of 150–250 EJ yr^{-1} of bioenergy feedstock with three integrated assessment models (Popp *et al.*, 2014; Rose *et al.*, 2014). The projected bioenergy cropland from this study is 450 to 550 Mha, comparable to our bioenergy cropland projections for producing 300 EJ yr^{-1} of 490 Mha (BE) to 690 Mha (BE_RF).

Prohibiting irrigated bioenergy production leads to an increase in bioenergy supply prices. In a market economy, such price increases would lead to a decreased demand for bioenergy and could reduce the additional land requirements in a rainfed-only bioenergy production scenario. The feedback of increased bioenergy prices on bioenergy demand depends crucially on the willingness-to-pay for bioenergy in the energy system. Rose *et al.* (2014) suggest that bioenergy is an economically attractive energy carrier, especially in combination with carbon capture and storage under climate change mitigation scenarios. Klein *et al.* (2014) find a high willingness-to-pay for bioenergy in case of stringent climate targets. Our sensitivity analysis demonstrates that bioenergy demand would need to decrease by 30% in BE_RF compared to BE to avoid bioenergy area expansion compared to BE.

Additional land requirements for bioenergy production in the rainfed-only case are partly fulfilled at the expense of pasture areas. While bioenergy expansion into pasture areas can lead to the loss of important ecosystems featuring high biodiversity (Alkemade *et al.*, 2013) and carbon storage potential (Conant *et al.*, 2001), the impact on natural forests is even more worrisome. Our results suggest that a rainfed-only bioenergy scenario would lead to substantially increased losses of natural forests (580 Mha) compared to the unrestricted bioenergy scenario (420 Mha), especially in tropical regions where additional forest losses in BE_RF compared to BE amount to 120 Mha by 2095. Tropical rainforests are high priority conservation targets since they are major biodiversity hotspots (Barlow *et al.*, 2007) and provide a number of important ecosystem services such as carbon sequestration and water flow regulation

(Onaindia *et al.*, 2013). It is thus likely that protecting freshwater ecosystems from degradation due to bioenergy production will accelerate the loss of important land ecosystems if no strict land-use change regulations are implemented.

Aside from the trade-off between water and land resources for bioenergy production, economic considerations may form an obstacle to the implementation of water-saving bioenergy production policies. With rising energy prices, bioenergy production may become an important source of income for farmers (Walsh *et al.*, 2003), and can play a key role for economic development in developing countries (Demirbas & Demirbas, 2007). We find that restricting irrigation changes the comparative advantages between regions and leads to reallocation of production and associated economic benefits.

Assumptions and limitations

This study investigates implications of different bioenergy production strategies on land and water resources in a cost optimization framework with a fixed bioenergy target of ~300 EJ yr^{-1} in 2095. While this setup allows us to investigate the cost optimal resource allocation as well as bioenergy supply prices for a fixed bioenergy demand under different production scenarios, we are not able to quantify price-induced changes in bioenergy demand between the scenarios. Thus, this study provides insights into the implications of substituting water resources with land resources for large-scale bioenergy production, but does not claim to provide a comprehensive picture of future bioenergy related resource requirements under different scenarios.

The influence of bioenergy production on water resources is not restricted to irrigation water requirements. First, water is also needed during the conversion of biomass into final energy (e.g., electricity, fuel, heat, Singh *et al.*, 2011). Processing requirements are however small compared to water requirements during feedstock production (Berndes, 2002; Gerbens-Leenes *et al.*, 2009; Gheewala *et al.*, 2011) and have therefore been neglected in this analysis. Second, bioenergy plantations will to some extent alter the balance between runoff and evapotranspiration, thereby changing available blue water in rivers, lakes and aquifers (Berndes, 2002). The magnitude of this effect is however highly uncertain (Haddeland *et al.*, 2011) and depends on the location and the type of vegetation that is replaced by bioenergy crops (Berndes, 2002). Quantifying the overall effect of bioenergy on water availability would therefore require a full coupling to a global vegetation and hydrology model such as LPJmL, which is beyond the scope of this analysis. Third, we focus on water quantity and do not investigate bioenergy implications for water quality.

Land requirements for bioenergy production crucially depend on bioenergy yields (Creutzig *et al.*, 2014). Observed bioenergy yields on test sites in Europe range between 120 and 280 GJ ha^{-1} yr^{-1} (Chum *et al.*, 2011). Average European bioenergy yields in 1995 in our model of 115 GJ ha^{-1} yr^{-1} (rainfed) and 220 GJ ha^{-1} yr^{-1} (irrigated) are consistent with these observations. It is however unclear, if the yields that were achieved under test conditions can be realized over large areas (Johnston *et al.*, 2009). Due to investments into agricultural research and development, all agricultural yields – including bioenergy yields – in our projections approximately double until the end of the century on global average. This yield projection is consistent with historical data on yield increases for conventional crops. It is however unclear, whether plant physiological limits will limit future yield increases (Cassman, 1999). Moreover, almost half of the past yield increases can be attributed to harvest index improvements (Krausmann *et al.*, 2013). In the case of lignocellulosic bioenergy crops, all aboveground biomass can be used for energy production, so that increasing the harvest index is hardly possible (Searle & Malins, 2014). On the other hand, breeding of lignocellulosic bioenergy crops has just started, fostering the hope that significant yield improvements are possible (Chum *et al.*, 2011). Several studies argue that natural productivity poses an upper limit to bioenergy yields (Erb *et al.*, 2012; Smith *et al.*, 2012; Haberl *et al.*, 2013). Within our model, bioenergy yields in 2095 stay within the potential yield achievable under current best management as simulated by LPJmL, except for Latin America. In summary, rainfed bioenergy yields within our model of up to 450 GJ ha^{-1} yr^{-1} in 2095 are within the range reported by Haberl *et al.*(2010) (69–600 GJ ha^{-1} yr^{-1} in 2055), but bioenergy yields remain a key uncertainty of our analysis.

Restrictive land-use change policies that mainly aim at conserving natural forests (REDD) are discussed as an option to mitigate climate change (Angelsen *et al.*, 2009). Our scenarios do not contain a REDD policy and therefore allow conversion of forests and other natural vegetation into bioenergy plantations. Under scenarios with a REDD policy, such expansion would be strictly limited and could lead to stronger land productivity increases, reduced land-use implications of bioenergy but potentially higher bioenergy prices.

Aside from land productivity, water productivity is a key determinant of the resource requirements for large-scale bioenergy production (King *et al.*, 2013). In our standard model implementation, agricultural research and development is assumed to increase both, land and irrigation water productivity. This assumption is supported by various studies on crop water productivity (Kijne *et al.*, 2004; Rosegrant *et al.*, 2009; Molden *et al.*, 2010) and can be achieved by: minimizing losses in the water distribution system; increasing the ratio of transpiration to evaporation on the field; increasing plant water-use efficiency by breeding and improved management of all inputs. The extent of possible irrigation water productivity improvements is however uncertain, especially in already highly intensified agricultural systems. Our sensitivity analysis shows that agricultural water requirements are significantly higher if no improvements in irrigation water productivity can be realized. The competitiveness of irrigated bioenergy production and the possible doubling of agricultural water withdrawals due to bioenergy production is, however, robust with respect to different assumptions on water productivity.

Policy implications and conclusions

In the context of the presented results, it is important that policies to protect freshwater ecosystems from degradation due to bioenergy production are carefully designed and address the trade-off with land ecosystems and the economic incentives opposing sustainable water use. Certification schemes are one possibility to manage the water implications of bioenergy production (Fehrenbach, 2011). A certificate for rainfed bioenergy production would allow consumers to make an informed choice and could create a market incentive for less water intensive production. Governments could furthermore create direct incentives for rainfed bioenergy production through taxes and subsidies. South Africa has for example already decided to stop the support for bioenergy crops under irrigation (Moraes *et al.*, 2011).

Policies that aim at incentivizing rainfed bioenergy production are useful to protect water resources but neglect the trade-off with land resources and may therefore endanger land ecosystems. Rather than promoting rainfed-only bioenergy production, one could therefore restrict water use for bioenergy production to sustainable levels. Such an approach would require site specific estimates of how much water is required for a functioning ecosystem. Estimates of how much water needs to be reserved for environmental purposes – also called environmental flows – are already available (Smakhtin *et al.*, 2004; Poff *et al.*, 2010), although more research is needed to increase the accuracy of such estimates (Pastor *et al.*, 2013). The implementation of comprehensive water management strategies that take into account the different types of human water use and environmental flow requirements (Pahl-Wostl *et al.*, 2013) would allow irrigation of bioenergy where enough water resources are available. Thus, negative impacts of bioenergy production on water resources could be prevented while irrigation could still contribute to reducing land requirements for bioenergy crops. Ideally, such sustainable water management policies would be accompanied by forest protection policies that can further reduce the negative impacts of bioenergy production on natural land ecosystems (Popp *et al.*, 2011b).

Producing 300 EJ yr^{-1} of bioenergy from dedicated bioenergy crops is a very ambitious scenario (Creutzig *et al.*, 2014). Lower second generation bioenergy production will of course have less implications for land and water resources and may raise less sustainability concerns. Even with a lower contribution from dedicated crops, bioenergy can make an important contribution to the future energy mix since forestry and residues can provide 35–125 EJ yr^{-1} in 2050 already (Creutzig *et al.*, 2014). It is furthermore likely that market forces lead to a decreased bioenergy demand because of higher prices if irrigation of bioenergy crops is prohibited. This process could mitigate the negative impacts of water-saving bioenergy production strategies on land resources. Our results however suggest that a price-induced demand reduction of 30% would be necessary to fully compensate additional land requirements if irrigated bioenergy production is prohibited.

In summary, our results indicate that without dedicated water protection policies, large-scale bioenergy production from dedicated 2nd generation energy crops may lead to severe degradation of freshwater ecosystems. It is therefore crucial that the focus of bioenergy strategies shifts from land-use efficiency (Gheewala *et al.*, 2011) to a broader sustainability perspective including water resources. We find that prohibiting irrigated bioenergy crop production for water resources protection can lead to the loss of important natural land ecosystems, especially tropical forests. Policies that balance water- and land-use implications of large-scale bioenergy production are therefore needed. The concept of environmental flow protection is a promising avenue since it protects freshwater ecosystems while still allowing for irrigated bioenergy production to increase yields and thereby decrease the pressure on land ecosystems. Further research should aim at investigating additional implications of water-saving bioenergy production strategies that were not covered here. Those include feedbacks on bioenergy deployment in the energy system, as well as implications for the water cycle due to changes in evapotranspiration on bioenergy plantations.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Additional model description and results.

Trade-offs between land and water requirements for large-scale bioenergy production

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Supporting information

Contents

Additional model and scenario description

All simulations for this analysis have been carried out with the MAgPIE model revision 7423.

MAgPIE world regions

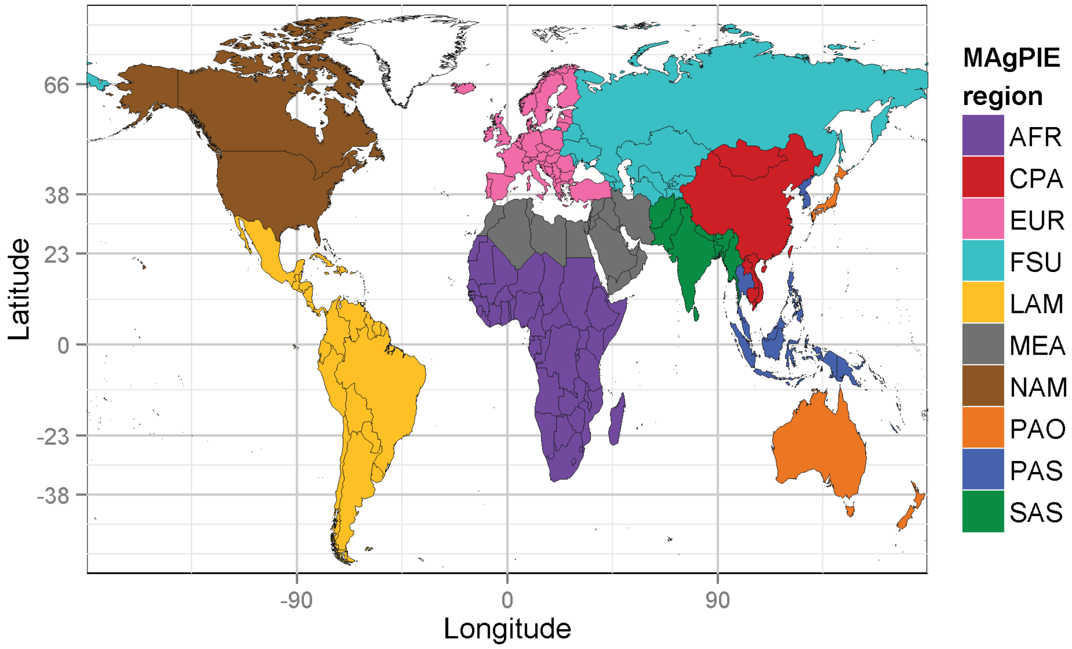

Figure S1 MAgPIE world regions. AFR=Sub Saharan Africa, CPA= centrally planned Asia including China, EUR=Europe, FSU=former Soviet Union, LAM=Latin America, MEA=Middle East and North Africa, NAM=North America, PAO=Pacific OECD, PAS=Pacific Asia, SAS=South Asia. Greenland and Antarctica are not covered by MAgPIE.

Bioenergy yields

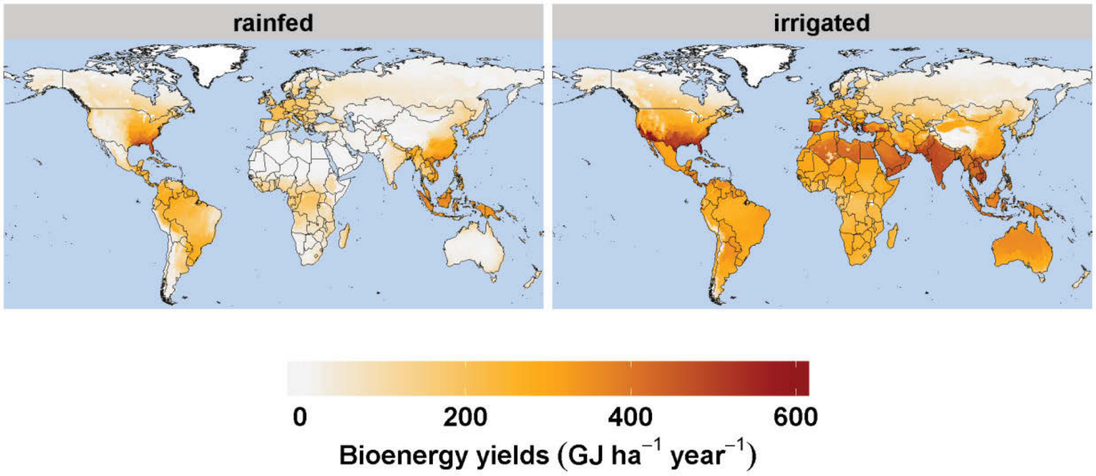

Figure S2 Yields of herbaceous lignocellulosic bioenergy crops in 1995. Rainfed (left) and irrigated (right). Bioenergy yields are derived from LPJmL potential yields (Beringer et al., 2011) and calibrated using information about observed land-use intensity (Dietrich et al., 2012) and agricultural yields (FAO, 2013) to arrive at actual yields. Note that actual yields are displayed for all land area except for Greenland and Antarctica, irrespective whether bioenergy is grown in a given location.

	WORLD	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
Rainfed (MAgPIE)	74	51	102	115	25	152	9	80	40	293	98
Irrigated (MAgPIE)	203	249	215	220	58	289	372	141	311	352	394
Calibration factor	-	0.26	0.58	0.71	0.37	0.38	0.41	0.72	0.34	0.47	0.46

Table S1 Global and regional average actual herbaceous bioenergy yields (GJ/ha/yr) in 1995. Top row: rainfed yields; middle row: irrigated yields. The average is obtained by calculating the non-weighted mean yield over all simulation units in a specific region, irrespective of whether bioenergy is actually grown. Bioenergy yields are derived from LPJmL potential yields (Beringer et al., 2011) and calibrated using information about observed land-use intensity (Dietrich et al., 2012) and agricultural area (FAO, 2013) to arrive at actual yields. Regional calibration factors are shown in the bottom row.

Non-agricultural water withdrawals

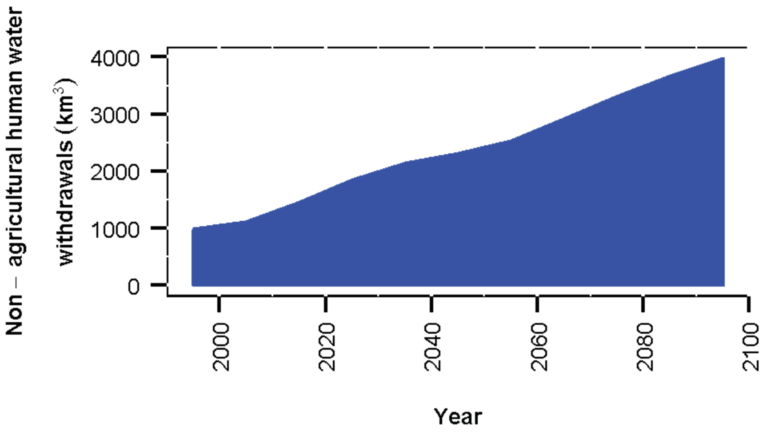

Figure S3 Global non-agricultural human water withdrawals including industrial production, domestic use and electricity production for the SSP2 scenario. Data is obtained from WaterGAP (Flörke et al., 2013), (Alcamo et al., 2003).

Demand

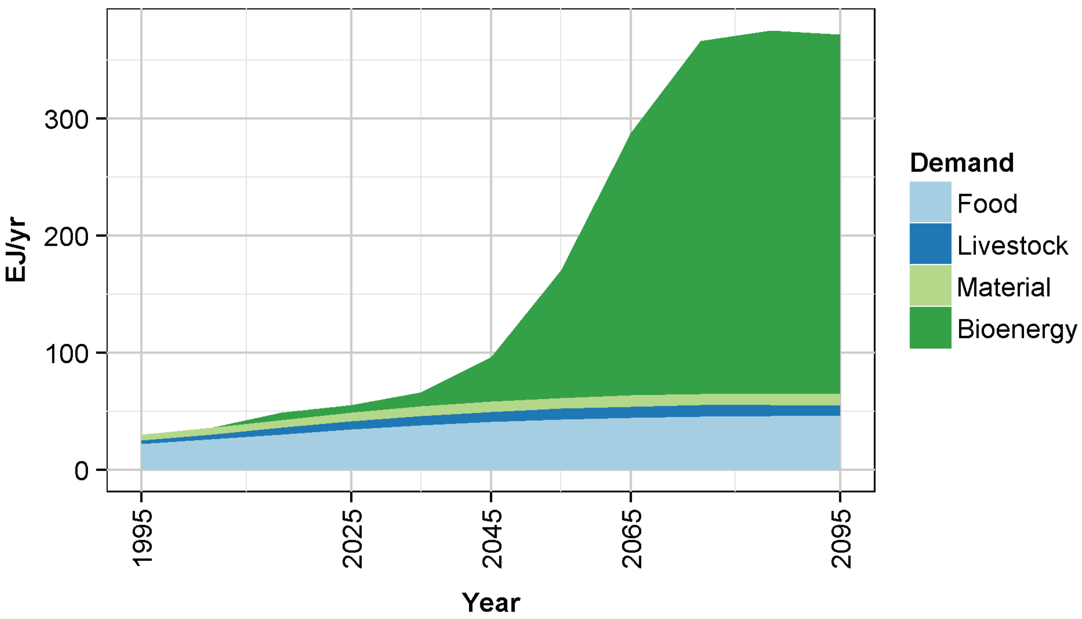

Figure S4 Time-series of global food, livestock, material and bioenergy demand in EJ per year. Food, livestock and material demand is calculated according to the methodology in Bodirsky et al. (under review) and Bodirsky et al. (2012) for the SSP2 scenario. Bioenergy demand is taken from Popp et al. (2011).

Available water calculation

Available water is based on simulations by the global hydrology, vegetation and crop growth model LPJmL (Rost et al., 2008; Müller and Robertson, 2014). LPJmL takes climate and precipitation data from the CRU 3.0 dataset (Mitchell and Jones, 2005) as input and simulates global runoff (water that enters rivers, lakes and aquifers) and river discharge on a 0.5 degree grid. Within MAgPIE, monthly runoff (also called "blue" water Rost et al., 2008), i.e. the renewable freshwater resource excluding fossil groundwater and discharge from melting glaciers constitutes available water in one month. Distribution of available water to individual grid cells follows an approach by Schewe et al. (2013) and uses river discharge as a weight. First, monthly available water is aggregated to river basin level (basins according to Döll and Lehner, 2002). Each grid cell in a river basin then receives a fraction of available water at basin level that corresponds to the ratio of the cell's monthly discharge over the total monthly discharge within the basin. It has been highlighted that a considerable fraction of blue water is inaccessible to humans due to seasonal distribution (Postel et al., 1996). It is common to assume that a fixed fraction of blue water is inaccessible and this fraction varies considerably among studies (Gerten et al., 2013). The focus of this analysis is on irrigation, thus we restrict the available water for irrigation to the growing period of the plants (based on LPJmL simulations). The annual water availability in each grid cell is thus the sum of the monthly values during the growing period except for cells where dams are present (Biemans et al., 2011) where the blue water resource of the whole year is available. We impose no further restrictions of available water such as ecosystem protection (Smakhtin et al., 2004). In total, 27000km^3 per year of water are available for human use globally.

Irrigation water requirement calculation

Irrigation water requirements for food, material and bioenergy crops is simulated by LPJmL based on the soil water deficit below optimal growth of the plants (Rost et al., 2008) on a 0.5 degree grid. These net irrigation requirements on the field are corrected for losses during the transport of the water from the source to the field. Based on a study by Rohwer et al. (2007), these conveyance losses were estimated at 36% of water withdrawn from the source.

Irrigation cost calculation

Irrigation costs comprise investment costs for deploying new irrigation infrastructure and annual costs for operating irrigation systems. Investment costs for irrigation for 1995 are based on Worldbank data (Jones, 1995) and enter the model on a regional level ranging from 1900 to

37200 US$ / ha. Jones (1995) finds that differences in costs between regions are largely driven by implementation problems (construction quality, procurement problems, and funding shortage). We assume that regional differences in institutional capacity will be reduced in the future. Therefore, costs linearly converge to the European level of 5700 US$ / ha until 2050 (Table S2).

	1995	2005	2015	2025	2035	2045	2055	2065	2075	2085	2095
AFR	37173	31444	25715	19986	14257	8528	5663	5663	5663	5663	5663
CPA	8781	8214	7647	7080	6514	5947	5663	5663	5663	5663	5663
EUR	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663
FSU	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663
LAM	12237	11042	9846	8651	7456	6261	5663	5663	5663	5663	5663
MEA	5933	5884	5835	5786	5737	5688	5663	5663	5663	5663	5663
NAM	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663
PAO	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663	5663
PAS	2078	2730	3382	4033	4685	5337	5663	5663	5663	5663	5663
SAS	1899	2584	3268	3952	4637	5321	5663	5663	5663	5663	5663

Table S2 Investment costs for installing new irrigation infrastructure (US$ / ha) for the MAgPIE regions.

Since no global dataset for annual costs for the operation and maintenance of irrigation systems is available, we use GTAP data (Narayanan et al., 2008) to calculate annual operation and maintenance costs. Calzadilla et al. (2011) have proposed an approach to split the GTAP land rent into the rent associated with irrigable land and the rent associated with irrigation water application. For this analysis, we use the rent associated with irrigation water application – calculated according to the approach by Calzadilla et al. – as a proxy for the operation and maintenance costs of irrigation infrastructure (Table S3). Local case studies in Africa and the US find annual irrigation costs of 10 – 404 US$ / ha and 167 – 392 US$ / ha respectively (Palanisami 1997; Schaible and Aillery 2013). 90% of the values resulting from our calculation are in the range reported by the local studies of 10 – 400 US$ / ha. High values of over 1000 US$ / ha only occur for potato in NAM and PAO.

	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
temperate cereals	31	109	96	34	48	39	51	70	97	56
tropical cereals	10	71	67	11	30	22	52	52	30	15
maize	10	55	46	19	17	52	53	78	20	15
rice	26	118	117	43	48	123	88	195	57	57
others	83	441	295	187	178	273	482	965	138	203
potato	332	695	805	389	396	764	1098	2011	609	696
cassava	46	162	94	72	72	397	92	230	67	129
pulses	59	271	280	177	81	125	220	248	153	104
soybean	21	80	105	20	77	76	71	105	36	40
rapeseed	222	400	597	92	304	325	246	439	728	229
groundnut	36	188	119	87	70	193	120	175	66	66
sunflower	105	398	243	141	286	140	199	229	196	125
oil palm	75	381	193	193	266	193	193	193	278	193
sugar beet	77	65	111	37	117	80	84	212	77	56
sugar cane	218	401	321	319	287	883	301	765	318	361
cotton	60	280	256	145	111	284	127	423	200	103

Table S3 Annual costs for operation and maintenance of irrigation systems (US$ / ha). Costs differ across regions and crops.

Additional results

Regional land-use change

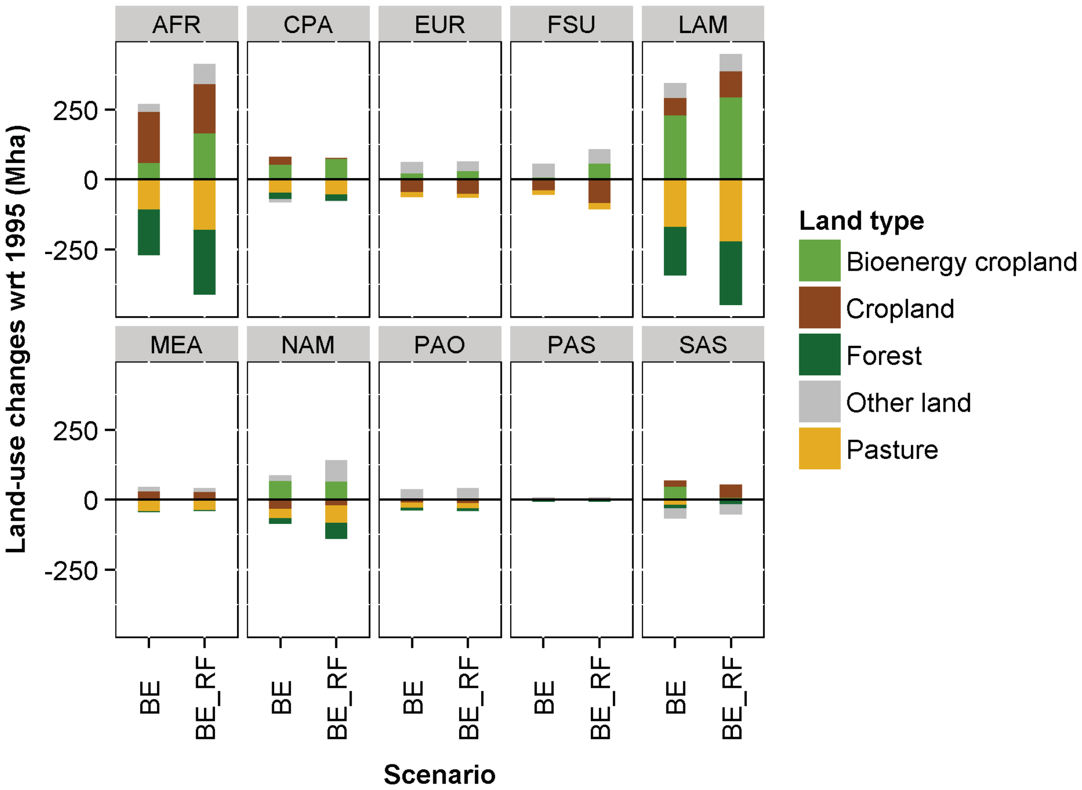

Figure S5 Regional land-use changes by the year 2095 with respect to 1995 for BE and BE_RF for the land types represented in MAgPIE. Total cropland is split into bioenergy cropland and cropland for food, feed and material production (Cropland). Positive values indicate an increase, negative values a decrease in the corresponding land pool.

Carbon emissions from land-use change

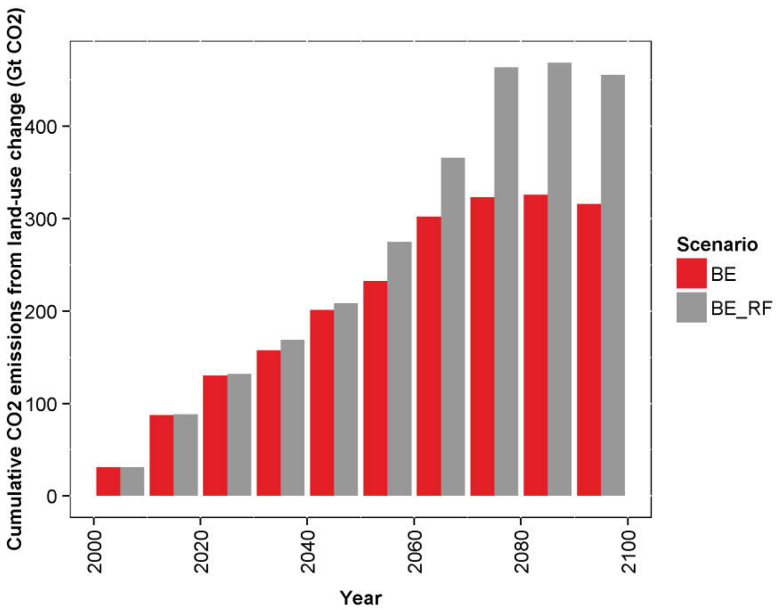

Figure S6 Global cumulative carbon dioxide emissions from land-use change for BE and BE_RF. The reference year is 1995.

Cropland validation

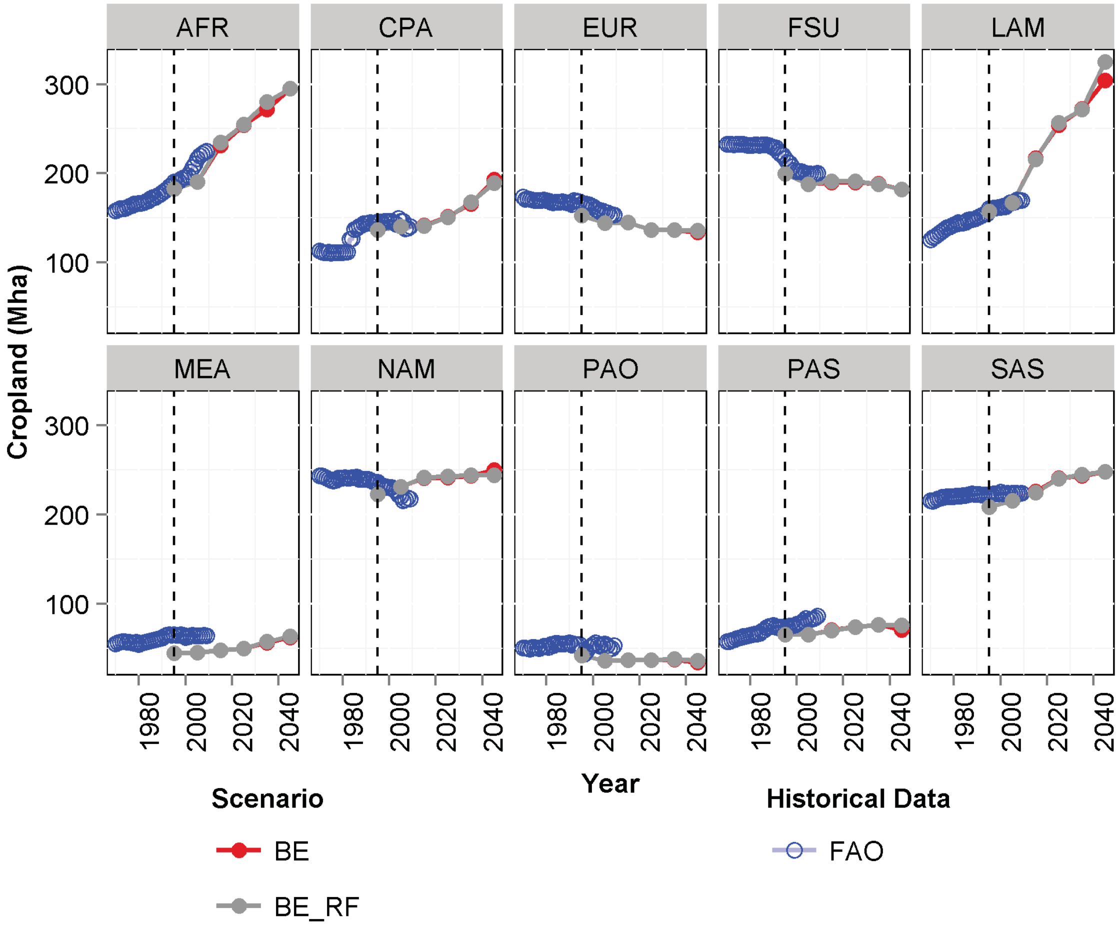

Figure S7 Regional cropland for BE and BE_RF. Historical data from FAO (FAO, 2013) is displayed for comparison. The vertical dashed line marks the start of the simulation period.

Pasture validation

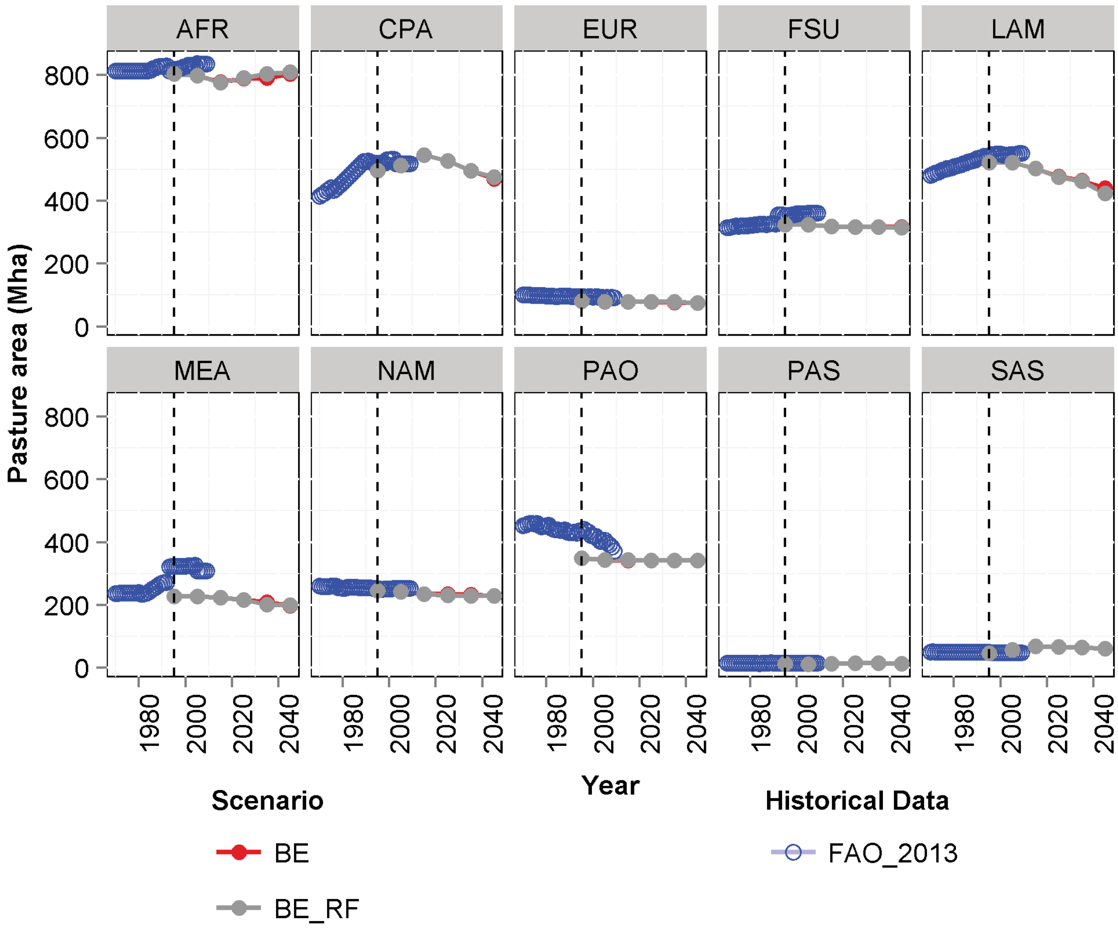

Figure S8 Regional pasture area for BE and BE_RF. Historical data from FAO (FAO, 2013) is displayed for comparison. The vertical dashed line marks the start of the simulation period.

Bioenergy yield development

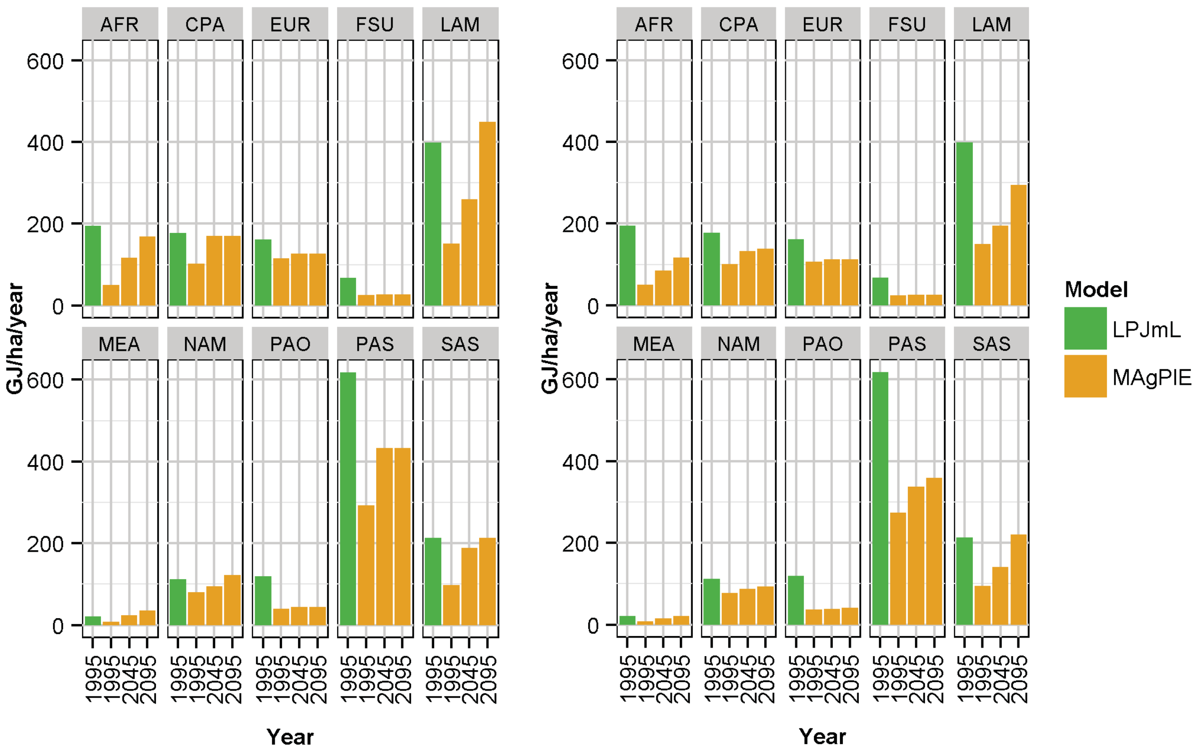

Figure S9 Herbaceous rainfed bioenergy yields for BE_RF over time for the 10 MAgPIE world regions. Standard model results (left) and results from the low Yields sensitivity model (right). Regional averages reflect the unweighted mean across all simulation units within a region. MAgPIE yields (yellow) increase over time due to technological change. LPJmL simulates potential yields under best currently available management options.

Bioenergy demand sensitivity

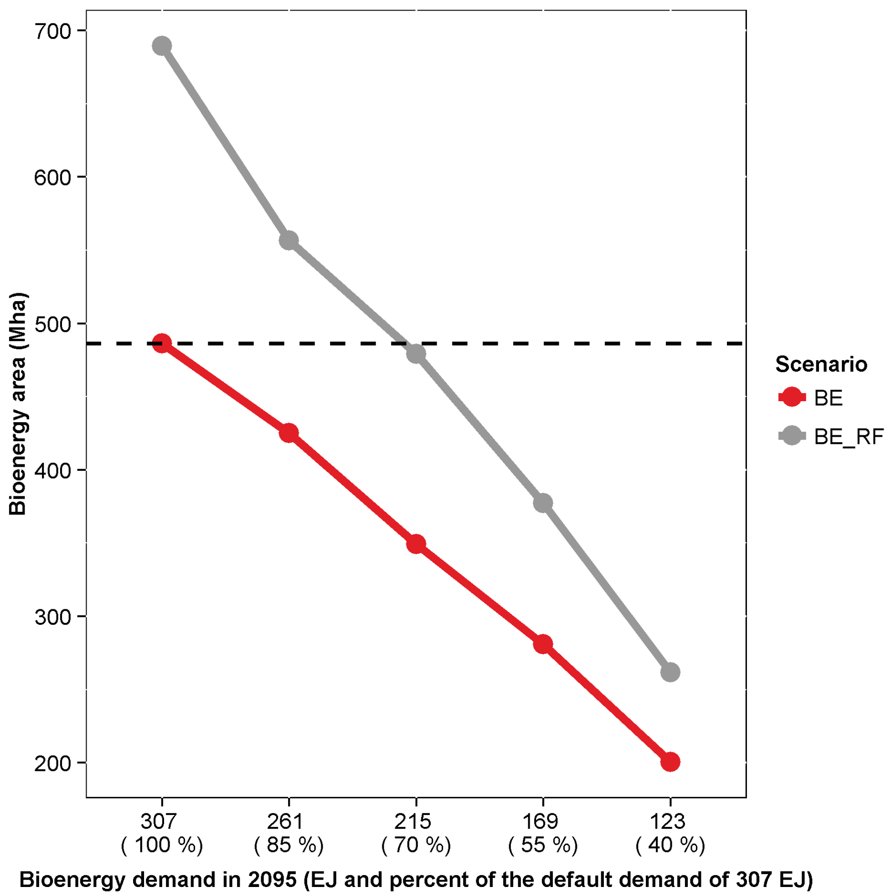

Figure S10 Global total bioenergy area in 2095 for BE and BE_RF under different bioenergy demand scenarios. Bioenergy demand scenarios are constructed by reducing the original demand in 15% steps from 100% (307 EJ/yr) to 40% (123 EJ/yr). The horizontal dashed line marks the bioenergy area for a demand of 307 EJ/yr in the BE scenario. In BE_RF, bioenergy area at a demand corresponding to 70% of the default value (307 EJ/yr) is equal to bioenergy area in BE with the full demand.

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V Investigating afforestation and bioenergy CCS as climate change mitigation strategies*

Authors:
Florian Humpenöder, Alexander Popp, Jan Philipp Dietrich, David Klein, Hermann Lotze-Campen, Markus Bonsch, Benjamin Leon Bodirsky, Isabelle Weindl, Miodrag Stevanovic and Christoph Müller

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Investigating afforestation and bioenergy CCS as climate change mitigation strategies

Florian Humpenöder[1,2], Alexander Popp[1], Jan Philip Dietrich[1], David Klein[1,2], Hermann Lotze-Campen[1], Markus Bonsch[1,2], Benjamin Leon Bodirsky[1,2], Isabelle Weindl[1,3], Miodrag Stevanovic[1,2] and Christoph Müller[1]

[1] Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany
[2] Technical University of Berlin, Berlin, Germany
[3] Humboldt University of Berlin, Berlin, Germany

E-mail: florian.humpenoeder@pik-potsdam.de

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Abstract

The land-use sector can contribute to climate change mitigation not only by reducing greenhouse gas (GHG) emissions, but also by increasing carbon uptake from the atmosphere and thereby creating negative CO_2 emissions. In this paper, we investigate two land-based climate change mitigation strategies for carbon removal: (1) afforestation and (2) bioenergy in combination with carbon capture and storage technology (bioenergy CCS). In our approach, a global tax on GHG emissions aimed at ambitious climate change mitigation incentivizes land-based mitigation by penalizing positive and rewarding negative CO_2 emissions from the land-use system. We analyze afforestation and bioenergy CCS as standalone and combined mitigation strategies. We find that afforestation is a cost-efficient strategy for carbon removal at relatively low carbon prices, while bioenergy CCS becomes competitive only at higher prices. According to our results, cumulative carbon removal due to afforestation and bioenergy CCS is similar at the end of 21st century (600–700 $GtCO_2$), while land-demand for afforestation is much higher compared to bioenergy CCS. In the combined setting, we identify competition for land, but the impact on the mitigation potential (1000 $GtCO_2$) is partially alleviated by productivity increases in the agricultural sector. Moreover, our results indicate that early-century afforestation presumably will not negatively impact carbon removal due to bioenergy CCS in the second half of the 21st century. A sensitivity analysis shows that land-based mitigation is very sensitive to different levels of GHG taxes. Besides that, the mitigation potential of bioenergy CCS highly depends on the development of future bioenergy yields and the availability of geological carbon storage, while for afforestation projects the length of the crediting period is crucial.

S Online supplementary data available from stacks.iop.org/ERL/9/064029/mmedia

Keywords: climate change mitigation, afforestation, bioenergy, carbon capture and storage, land-use modeling, land-based mitigation, carbon sequestration

Introduction

For ambitious climate change mitigation, huge reductions in greenhouse gas (GHG) emissions are needed (Meinshausen *et al* 2009, Rogelj *et al* 2011, 2013a). Currently, the land-use sector is responsible for 17–32% of global anthropogenic GHG emissions (Bellarby *et al* 2008). There are several measures for reducing GHG emissions in the land-use sector, such as avoided deforestation or improved agricultural management (Smith *et al* 2013). However, the land-use sector cannot only contribute to climate change mitigation by decreasing GHG emissions, but also by increasing carbon uptake from the atmosphere (Rose *et al* 2012). Recent integrated assessment modeling (IAM) studies focused on afforestation and bioenergy in combination with carbon capture and storage (bioenergy CCS) as land-based mitigation strategies for carbon removal (Tavoni and Socolow 2013). Both strategies make use of the accumulation of carbon in growing biomass through photosynthesis. Bioenergy CCS removes carbon from the atmosphere by capturing the carbon released during the combustion of biomass and storing the captured carbon in geological reservoirs underground. Afforestation detracts carbon from the atmosphere through the managed regrowth of natural vegetation. While carbon removal due to bioenergy CCS can be raised through land expansion *and* yield increases (increase in productivity per unit area), gains in carbon removal due to afforestation are mostly limited to the extensification of forestland.

In the literature, studies focus on the standalone mitigation potential of bioenergy CCS (Azar *et al* 2010, Popp *et al* 2011, Klein *et al* 2014, Kriegler *et al* 2013, Vuuren *et al* 2013) and afforestation (Strengers *et al* 2008, Reilly *et al* 2012) or investigate both at the same time (Wise *et al* 2009, Calvin *et al* 2014, Edmonds *et al* 2013). However, the standalone and combined effects of bioenergy CCS and afforestation on land-use and carbon dynamics have not been analyzed so far with a common methodological approach. Looking at both, the standalone and combined mitigation potential, provides insight into potential trade-offs like competition for land or path dependencies, which are important for the evaluation of afforestation and bioenergy CCS as mitigation strategies. In this study, we use the Model of Agricultural Production and its Impacts on the Environment (MAgPIE), a spatially explicit, global land-use model to analyze three scenarios with different land-based mitigation policies: afforestation, bioenergy CCS and the combination of both. Land-based mitigation in MAgPIE is incentivized by an exogenously given tax on GHG emissions. The trade-off between land expansion and yield increases is treated endogenously in the model. In order to test the stability of our results, we perform sensitivity analyses with the most important exogenous parameters.

Methods and material

Land-use model MAgPIE

MAgPIE is a spatially explicit, global land-use allocation model and projects land-use dynamics in ten-year time steps until 2095 using recursive dynamic optimization (Lotze-Campen *et al* 2008, Popp *et al* 2010). The objective function of MAgPIE is the fulfilment of food, livestock and material demand at minimum costs under socio-economic and biophysical constraints. Demand is based on exogenous future population and income projections (see scenario section), while price-induced changes in consumption are not reflected. Major cost types in MAgPIE are: factor requirement costs (capital, labor and fertilizer), land conversion costs, transportation costs to the closest market, costs for R&D (technological change) and costs for GHG emission rights. For long term investments, like land conversion or R&D, we assume a time horizon of 30 years and an annual discount rate of 7%, which reflects the opportunity costs of capital at the global level (IPCC 2007, chapter 2.4.2.1). While socio-economic constraints like trade liberalization and forest protection are defined at the regional level (ten world regions) (figure S1), biophysical constraints such as crop yields, carbon density and water availability, derived from the global hydrology and vegetation model LPJmL (Bondeau *et al* 2007, Müller and Robertson 2014), as well as land availability (Krause *et al* 2013), are introduced at the grid cell level (0.5 degree longitude/latitude; 59 199 grid cells). Due to computational constraints, all model inputs in 0.5 degree resolution are aggregated to 500 clusters for the optimization process based on a k-means clustering algorithm (Dietrich *et al* 2013). During the optimization process, the cluster level is the finest resolution. The clustering algorithm combines grid cells to clusters based on the similarity of data for each of the ten world regions. If, for instance, two grid cells with similar land patterns are merged into one cluster, the algorithm preserves the land area available by summing up the area of the two grid cells. Investment in R&D in the agricultural sector translating into yield-increasing technological change is a variable in MAgPIE and can therefore endogenously enhance food and bioenergy crop yields (Dietrich *et al* 2014). Finally, the cost minimization problem is solved through endogenous variation of spatial production patterns, land expansion (both at the cluster level) and yield-increasing technological change (at the regional level) (Lotze-Campen *et al* 2010).

MAgPIE features land-use competition based on cost-effectiveness at cluster level among the land-use related activities food, livestock and bioenergy production as well as afforestation. Available land types are cropland, pasture, forest and other land (e.g. non-forest natural vegetation, abandoned agricultural land, desert). The forestry sector, in contrast to the agricultural and livestock sector, is currently not implemented dynamically in MAgPIE. Therefore, timberland needed for wood production, consisting of forest plantations and modified natural forest, is excluded from the optimization, which is about 30% of the initial global forest area (4235 mio ha). In addition, other parts of forestland, mainly undisturbed natural forest, are within protected forest areas, which is about 12.5% of the initial global forest area (FAO 2010). Altogether, about 86% of the world's land surface is freely available in the optimization of the initial time-step.

MAgPIE calculates emissions of the Kyoto GHGs carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) (Bodirsky *et al* 2012, Popp *et al* 2010, 2012). Mitigation of GHG emissions is stimulated by an exogenous tax regime on GHG emissions (see scenario section). The GHG tax is multiplied with GHG emissions in order to calculate GHG emission costs, which enter the cost minimizing objective

Table 1. Regional herbaceous bioenergy yields (GJ ha^{-1}) in 1995 derived from LPJmL (potential yields) and initial bioenergy yields MAgPIE (actual yields). Region specific yields are obtained by calculating the average across all clusters within a region.

	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
LPJmL	198	188	165	59	382	26	101	154	595	235
MAgPIE	52	105	125	21	150	9	71	48	251	110

function of MAgPIE. For instance, CO_2 emissions from land-use change can be reduced through avoided deforestation (carbon stock conservation). But unlike N_2O and CH_4 land-use emissions, CO_2 emission from the land-use system can become negative if photosynthetic carbon uptake from the atmosphere outweighs carbon release to the atmosphere from plant decomposition and land-use change (carbon stock increase). Therefore, land-based climate change mitigation via afforestation or bioenergy CCS is incentivized by the revenue from the GHG tax regime for carbon removal from the atmosphere. A detailed description of the underlying formulas is available in the supplementary data, available at stacks.iop.org/ERL/0/000000/mmedia. For the conversion of N_2O and CH_4 emissions into CO_{2eq} we use GWP100 (IPCC (2013)).

Bioenergy CCS

In MAgPIE, dedicated lignocellulosic biomass (rainfed only) can be converted to secondary energy via different conversion routes. The carbon released from biomass during combustion is captured and stored underground using CCS technology.

Herbaceous and woody bioenergy yields at grid cell level for the initialization of MAgPIE are derived from LPJmL (Beringer *et al* 2011). While LPJmL simulations supply data on potential yields, i.e. yields achieved under the best currently available management options, MAgPIE aims to represent actual yields. Therefore, LPJmL yields are reduced using information about observed land-use intensity (Dietrich *et al* 2012) and agricultural area (FAO 2013). For instance, in China (CPA) herbaceous bioenergy yields from LPJmL are reduced by about 45% to obtain actual yields for the initialization of MAgPIE (table 1). MAgPIE bioenergy yields can exceed LPJmL bioenergy yields over time as endogenous investments in R&D push the technology frontier. Higher bioenergy yields are associated with increased carbon uptake from the atmosphere per unit area.

Bioenergy CCS can provide energy and remove carbon from the atmosphere at the same time. Due to this versatility, bioenergy CCS is an attractive mitigation option in scenarios with ambitious climate targets. The largest share of profits in these scenarios comes from the carbon sequestration and not from the energy portion of the bioenergy CCS technology (Rose *et al* 2014). In this study, we focus on the carbon removal potential of bioenergy CCS and therefore disregard the value of the energy produced. We implemented three different conversion routes with CCS technology in the model: biomass to hydrogen (B2H2), biomass integrated gasification combined cycle and biomass to liquid (B2L) (Klein *et al* 2014). Levelized costs of energy (LCOEs) are calculated using the time horizon of 30 years and the discount rate of 7% (see MAgPIE description), which are both within the range of common assumptions for LCOE calculations (IEA and OECD NEA 2010, chap 2.3). The LCOEs include initial investment costs in infrastructure as well as operational and maintenance costs. The B2H2 technology in combination with CCS features a higher conversion efficiency (55%) and carbon capture rate (90%) at lower LCOEs (8 \$ GJ^{-1}) than the other available technologies (based on Klein *et al* 2014). Demand for bioenergy in this study does not rely on exogenous trajectories, but is derived endogenously as a response to the GHG tax, which rewards carbon removal due bioenergy CCS, while the value of energy produced due to bioenergy CCS is disregarded. The cost minimizing objective function of MAgPIE in combination with carbon removal being the only incentive in the model to employ bioenergy CCS renders the B2H2 technology superior to the other available conversion routes. The geological carbon storage capacity is constrained at the regional level (table S3), which adds up to 3960 $GtCO_2$ at the global level (Bradshaw *et al* 2007). We assume a lifetime of the CCS technology of 200 years (Szulczewski *et al* 2012) and therefore limit the annual geological injection of carbon to 0.5% yr^{-1} in terms of the geological carbon storage capacity, which results in an annual realizable geological injection rate of about 20 $GtCO_2\ yr^{-1}$ globally. As biomass can be traded, the location of geological carbon storage can differ from the location of biomass production. Levelized costs for transportation and injection of captured carbon are at 9 \$/tCO_2 (Klein *et al* 2014).

Afforestation

Compared to bioenergy CCS, afforestation can be considered as low-tech land-based mitigation strategy, since no technical infrastructure for processing is needed. In MAgPIE, afforestation is a managed regrowth of natural vegetation. The regrowth is managed in that way as endemic seed sources are put in place manually as part of the land conversion process. Regrowth of natural vegetation affects vegetation, litter and soil carbon stocks, which are calculated as the product of carbon density and afforestation area (see online supplementary data for details). Vegetation, litter and soil carbon density of potential natural vegetation in 1995 at grid cell level is derived from LPJmL (figure S4). Vegetation carbon density increases over time along S-shaped growth curves (figure 1). The vegetation carbon density growth curves are based on a Chapman–Richards volume growth model (Murray and von Gadow 1993, Gadow and Hui 2001), which is parameterized using vegetation carbon density of potential natural vegetation (figure S4(a)) and climate region specific

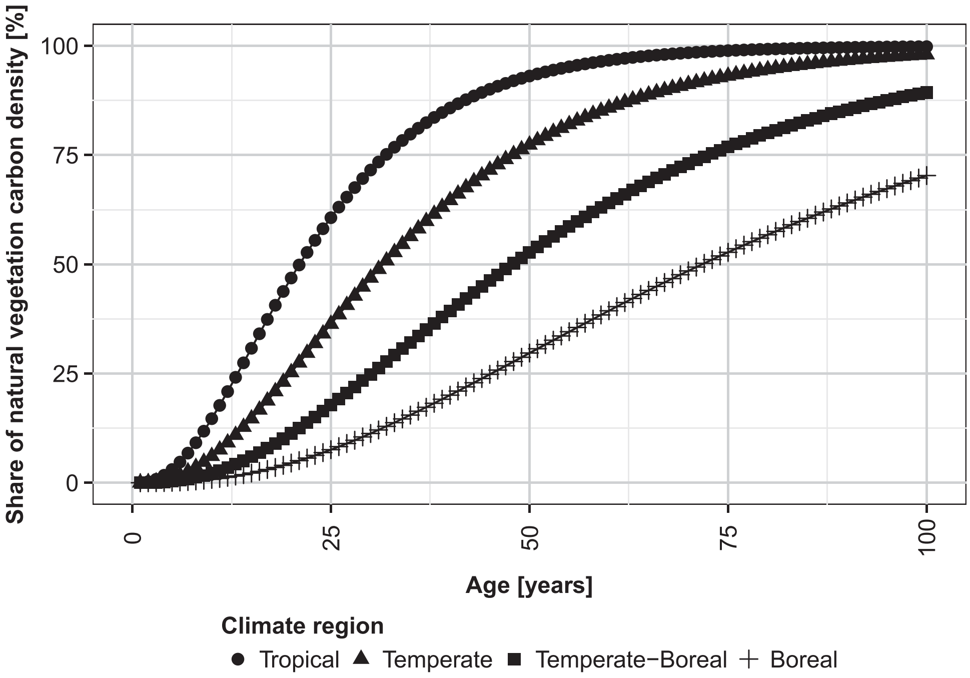

Figure 1. Climate region specific S-shaped vegetation carbon density growth curves for a period of 100 years. The vertical axis presents the share of grid-cell specific vegetation carbon density of potential natural vegetation in 1995 (figure S4a).

mean annual increment (MAI) and MAI culmination age (IPCC 2006). Litter and soil carbon density are assumed to increase linearly towards the value of potential natural vegetation (figures S4(b) and (c)) within a 20 years time frame (IPCC 2000). The initial value for vegetation and litter carbon density is assumed to be 0, while the initial grid-cell specific value for soil carbon density is the average between cropland and potential natural vegetation soil carbon density.

In MAgPIE, the decision to invest in afforestation depends on the benefit-cost ratio over the time horizon of 30 years, which is a common crediting period for afforestation projects (United Nations 2013). Firstly, cumulative carbon uptake over the time horizon is calculated as the product of new afforestation area and carbon density (vegetation, litter and soil) at age 30. Secondly, the benefit of an afforestation activity is calculated as the product of this cumulative carbon uptake 30 years ahead and the level of the current GHG tax (see online supplementary data for more details). Finally, for comparability with the annual bioenergy CCS activity, this future cash flow is annualized using the discount rate of 7% (see MAgPIE description). Land conversion and management costs are based on Sathaye *et al* (2005). Regional costs for the conversion of any land type into afforestation land range between 849 $ ha^{-1} (SAS) and 2484 $ ha^{-1} (NAM) (table S2) in the initial time step and are proportionally scaled with GDP for future time steps. Total land conversion costs are annualized. Annual management costs range between 2 $ ha^{-1} yr^{-1} (FSU) and 127 $ ha^{-1} yr^{-1} (AFR). Contrary to bioenergy CCS, technological change has no direct effect on the carbon removal potential of afforestation.

Scenarios

Our scenarios are based on the shared socio-economic pathways (SSPs) for climate change research (O'Neill *et al* 2014). It should be noted that the SSPs do not incorporate climate mitigation policies by definition. In this study, we choose SSP 2, a 'Middle of the Road' scenario with intermediate socio-economic challenges for adaptation and mitigation. Food, livestock and material demand (figure S2) is calculated using the methodology described in Bodirsky *et al* and the SSP 2 population and GDP projections (IIASA 2013).

We assume a GHG tax (Tax30) on Kyoto gases (CO_2, N_2O, CH_4) that increases nonlinearly at a rate of 5% yr^{-1} (Kriegler *et al* 2013). The GHG tax has a level of 30 $/t$CO_{2eq}$ in 2020 and starts in 2015 (figure S3). The resulting GHG tax with prices of 102 $/t$CO_{2eq}$ in 2045 and 1165 $/t$CO_{2eq}$ in 2095 is close to GHG price trajectories required to limit global average temperature increase to 2 °C above pre-industrial levels with a probability of 50% (Rogelj *et al* 2013b). Due to this ambitious climate change mitigation target, biophysical climate impacts on crop yields and carbon densities are assumed to be weak and are therefore not regarded in this study.

We investigate four scenarios, which cover two dimensions: GHG tax and availability of carbon removal options (table 2). In the business as usual scenario (BAU), no tax on GHG emissions is applied, i.e. there is no incentive to avoid GHG emissions. In the mitigation scenarios, the GHG tax penalizes all positive GHG emissions from the land-use system and rewards negative CO_2 emissions from afforestation in AFF, from bioenergy CCS in BECCS, and from both in AFF+BECCS.

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Sensitivity analysis

To address the uncertainty in exogenous model parameters, we investigate the sensitivity of our simulations to changes in model parameterization. Crucial parameters in the context of this study are the geological carbon storage capacity (CCS capacity), the GHG tax, the time horizon for investment decisions, the discount rate, and assumptions about future bioenergy yields. Table 3 summarizes the parameter settings for the sensitivity analysis.

CCS capacity: Bradshaw *et al* (2007) estimates a range for geological carbon storage capacity at the global level of 100–200 000 $GtCO_2$. For DEFAULT, we use 3960 $GtCO_2$. For the sensitivity analysis we vary this value by factor 20 in both directions (198 $GtCO_2$ in LOW, 79 200 $GtCO_2$ in HIGH). Based on Szulczewski *et al* (2012), we assume a lifetime of CCS of 200 years. Therefore, we limit the annual injection of carbon to 0.5% yr^{-1} in terms of the total CCS capacity. For DEFAULT this results in 20 $GtCO_2$ of the total CCS capacity, for LOW in 1 $GtCO_2$ yr^{-1} and for HIGH in 396 $GtCO_2$ of the total CCS capacity globally.

Table 2. Scenario definitions; GHG tax: Tax30 has a level of 30 $/$tCO_{2eq}$ in 2020, starts in 2015 and increases by 5% yr^{-1}; carbon removal option(s): available option(s) for generating negative CO_2 emissions rewarded by the GHG tax.

	GHG tax	Carbon removal option(s)
BAU	—	—
AFF	Tax30	Afforestation
BECCS	Tax30	Bioenergy CCS
AFF +BECCS	Tax30	Afforestation and bioenergy CCS

GHG tax: in DEFAULT, the GHG tax has a level of 30 $/$CO_{2eq}$ in 2020, starts in 2015 and increases by 5% yr^{-1}. For LOW and HIGH, the level of the GHG tax is 5 and 50 $/$tCO_{2eq}$ in 2020 respectively. The range for the sensitivity analysis is based on Kriegler *et al* (2013).

Time horizon: in DEFAULT, the time horizon for investments is 30 years, which is common in the energy sector as well as for afforestation projects. For LOW and HIGH we chose 10 and 50 years respectively (IEA and OECD NEA 2010, United Nations 2013).

Discount rate: in DEFAULT, the annual discount rate is 7%, which reflects the opportunity costs of capital at the global level. For the sensitivity analysis, we vary the discount rate by 3% points in both directions, based on a literature range of 4–12% (IPCC (2007), chap 2.4.2.1).

Bioenergy yields: in DEFAULT, bioenergy yields are variable and assumed to increase, along with food crop yields, due to endogenous technological change in the agricultural

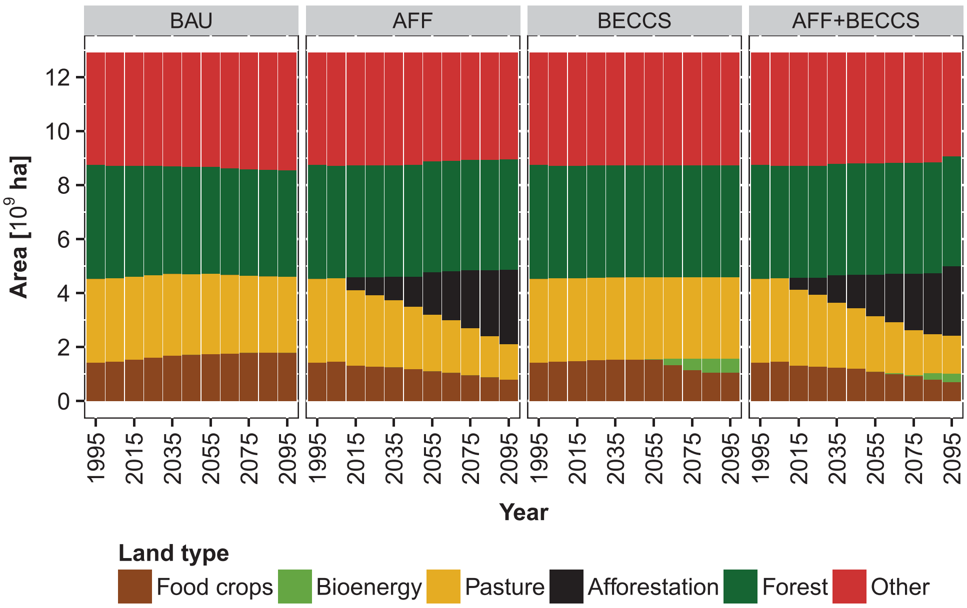

Figure 2. Time-series of global land-use pattern (10^9 ha) for BAU, AFF, BECCS and AFF+BECCS and six land types.

Table 3. Parameter settings for sensitivity analysis. 'DEFAULT' characterizes our default parameter settings used in this study. 'LOW'/'HIGH' characterize lower/higher parameter values compared to 'DEFAULT'.

	CCS capacity globally [Gt CO_2]	GHG tax in 2020 (2095) [US$/$tCO_{2eq}$]	Time horizon [Years]	Discount rate [% yr^{-1}]	Bioenergy yields [–]
LOW	198	5 (194)	10	4	Static
DEFAULT	3960	30 (1165)	30	7	Variable
HIGH	79200	50 (1942)	50	10	—

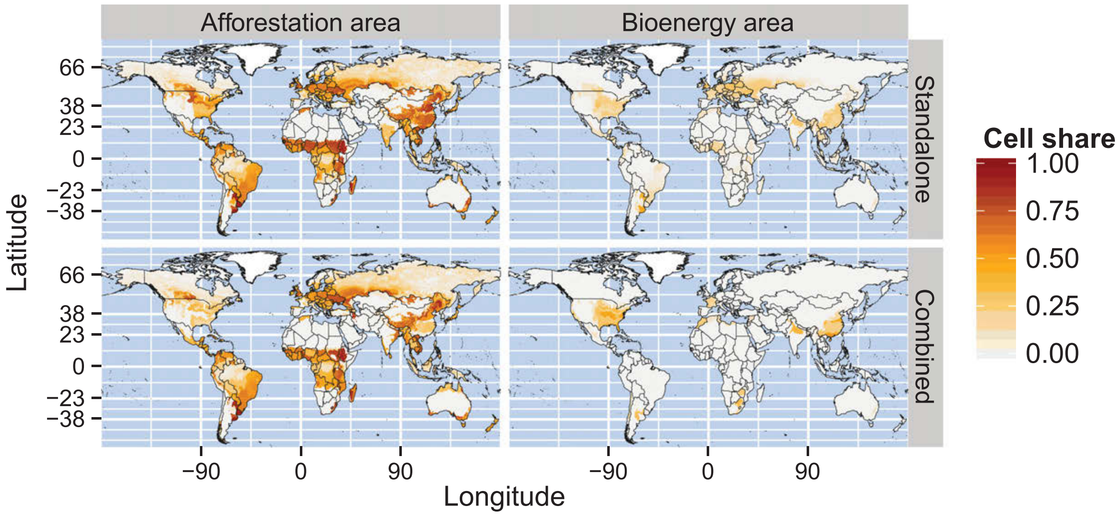

Figure 3. Grid-cell specific share of afforestation and bioenergy area in the standalone scenarios (top) and the combined setting (bottom) in 2095. Colors indicate the share of afforestation or bioenergy area in each cell. Grid-cell specific results are obtained by disaggregation of cluster level results (each grid cell is assigned the value of the cluster it belongs to).

sector. In LOW, technological change in the agricultural sector has no impact on bioenergy crop yields (i.e. bioenergy yields are fixed at the initial level), while food crop yields can still increase due to technological change.

To investigate the role of the algorithm used for clustering our high resolution input data, we perform sensitivity analysis with different numbers of spatial cluster units (100–500) in addition.

Results

Land-use dynamics

In 1995, total land cover (12 907 mio ha) consists of food crop (1425 mio ha), pasture (3073 mio ha), forest (4235 mio ha) and other land (4174 mio ha) (figure 2). In the BAU scenario (no GHG tax), food crop area increases by about 300 mio ha until 2095, mainly at the expense of forestland. In the second half of the century, pasture area decreases due to stabilizing livestock demand (figure S2) in combination with average yield increases of about 0.48% yr^{-1} (figure S10), leading to an increase of abandoned agricultural land. In the mitigation scenarios, the GHG tax on land-use change emissions keeps forestland almost constant over time. Afforestation emerges as cost-efficient mitigation strategy from 2015 (start of GHG tax at 24 \$/tCO_{2eq}) and increases, mainly at the expense of pasture and food crop area, to 2773 mio ha in AFF until 2095. Endogenous yield increases, accompanied by changes in spatial production patterns, compensate for the reduced agricultural area. In AFF, the cost–efficient level of average yield increases in the agricultural sector is 1.21% yr^{-1} throughout the 21st century (figure S10). Bioenergy CCS comes into play much later than afforestation, as it is cost-efficient first in 2065 (270 \$/tCO_{2eq}). Bioenergy area increases to 508 mio ha until 2095 in BECCS, mainly at the expense of food crop area. Total dedicated bioenergy production, mainly herbaceous crops, stabilizes at 237 EJ yr^{-1} until 2095 (figures S6, S7). In the combined setting, AFF+BECCS, afforestation area (2566 mio ha) is slightly smaller compared to AFF, while bioenergy area (300 mio ha) is almost halved compared to BECCS. Despite the smaller bioenergy area, bioenergy production remains at 237 EJ yr^{-1} in 2095 in AFF +BECCS, which is reflected in a higher level of average yield increases in AFF+BECCS (1.37% yr^{-1}) compared BECCS (1% yr^{-1}) (figure S10).

The maps in figure 3 illustrate the spatial distribution of afforestation and bioenergy area for the standalone scenarios (AFF/BECCS) and the combined setting (AFF+BECCS) in 2095. In the standalone scenarios, afforestation area is found in many world regions, predominantly in Sub-Sahara African, Latin America, China, Europe and the USA, while bioenergy area is mostly found in the northern hemisphere in the USA, China and Europe. In the combined scenario, afforestation area is similar to AFF. But due to competition for land between the two carbon removal options, afforestation area is reduced in favor of bioenergy area in the USA and China in AFF+BECCS. There are several reasons why the USA, China and Europe are the main bioenergy producers. We provide insight in subsection '*Bioenergy CCS and the role of yield increases*' along with figure 5.

Carbon dynamics

In the BAU scenario, CO_2 emissions from the land-use system accumulate to 177 GtCO_2 until 2095 (figure 4). The peak in mid-century is mainly caused by deforestation, while the following decline in CO_2 emissions is due to ecological succession on abandoned agricultural land. In the mitigation scenarios, the described land-use dynamics lead to net carbon removal from the atmosphere. More precisely, carbon is detracted from the atmosphere by photosynthesis and is either

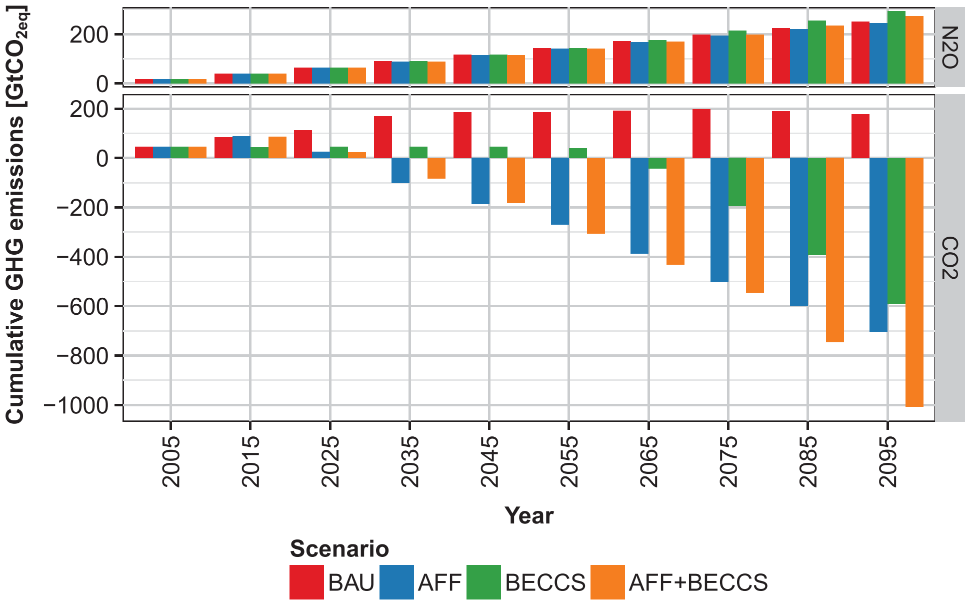

Figure 4. Time-series of global cumulative N_2O and CO_2 emissions ($GtCO_{2eq}$) from the land-use system for BAU, AFF, BECCS and AFF +BECCS.

biologically sequestered via afforestation or geologically sequestered via bioenergy CCS. In AFF, land conversion into afforestation area increases cumulative CO_2 emissions in 2015, followed by continuous carbon removal of about 10 $GtCO_2\ yr^{-1}$ throughout the 21st century. Until 2095, carbon removal in AFF accumulates to 703 $GtCO_2$. In BECCS, cumulative CO_2 emissions are almost constant until bioenergy CCS becomes cost-efficient as mitigation strategy in 2065 at GHG prices of 270 $/t$CO_{2eq}$. From 2065, carbon removal in BECCS is about 20 $GtCO_2\ yr^{-1}$, which cumulates to 591 $GtCO_2$ until 2095. In AFF+BECCS, carbon dynamics are similar to AFF until bioenergy CCS becomes competitive as mitigation option in addition to afforestation in 2055. Carbon removal in AFF+BECCS is about 25 $GtCO_2\ yr^{-1}$ in from 2065 to 2095, which results in cumulative carbon removal of 1000 $GtCO_2$ until 2095. In 2095 in BECCS and AFF+BECCS, the constraint on the annual geological carbon injection rate is binding (20 $GtCO_2\ yr^{-1}$), while cumulative carbon storage capacity (3960 $GtCO_2$) would last for approximately another 150 years.

Bioenergy CCS and the role of yield increases

Contrary to afforestation, the carbon removal rates per unit area of bioenergy CCS can be enhanced through yield increases. Figure 5 illustrates the potential annual carbon removal rates during the optimization for 1995 and 2095 in the AFF+BECCS scenario, i.e. the annual carbon removal rates shown here represent realizable, but not necessarily realized, carbon removal rates (compare to figure 3). In the remainder of this subsection, we talk about annual realizable carbon removal rates. In 1995, afforestation shows higher carbon removal rates than bioenergy CCS in the majority of cells, with highest carbon removal rates in the tropics (about 20 tC $ha^{-1}\ yr^{-1}$). In 2095, the picture is fundamentally different due to yield-increasing technological change on bioenergy crops, which increases carbon removal per unit area. In AFF +BECCS, average yield-increase throughout the century is at 1.38% yr^{-1} (figure S10), which more than triples initial bioenergy yields until 2095 (figure S5). By end-of-century bioenergy CCS exceeds the carbon removal rates of afforestation in the tropics (about 25–30 tC $ha^{-1}\ yr^{-1}$). However, bioenergy production does not take place in the tropics but mainly in the USA, China and Europe (figure 3) for three reasons. First of all, the USA and China exhibit higher carbon removal rates in 2095 (about 30–40 tC $ha^{-1}\ yr^{-1}$) compared to the tropics. Second, the tropical regions are the most attractive places for afforestation. Third, bioenergy production relies on transport infrastructure, which is much more sophisticated in Europe, USA and China than in the tropics (Nelson 2008). Bioenergy yield gains go along with increased fertilizer use, which drives N_2O emissions. In 2095, cumulative N_2O emission in BECCS and AFF +BECCS are about 30–50 $GtCO_{2eq}$ higher compared to BAU or AFF (figure 4), although N_2O emissions are penalized by the GHG tax.

Sensitivity analysis

In order to test the stability of our results, we perform sensitivity analyses with crucial exogenous parameters (table 3). Figure 6 shows the results in terms of land and carbon dynamics at the global level. Regional results can be found in figure S8.

The constraint on the annual geological carbon injection rate is crucial for the scenarios with bioenergy CCS. With 1 $GtCO_2\ yr^{-1}$ and 20 $GtCO_2\ yr^{-1}$ the constraint is binding, which indicates that the mitigation potential of bioenergy

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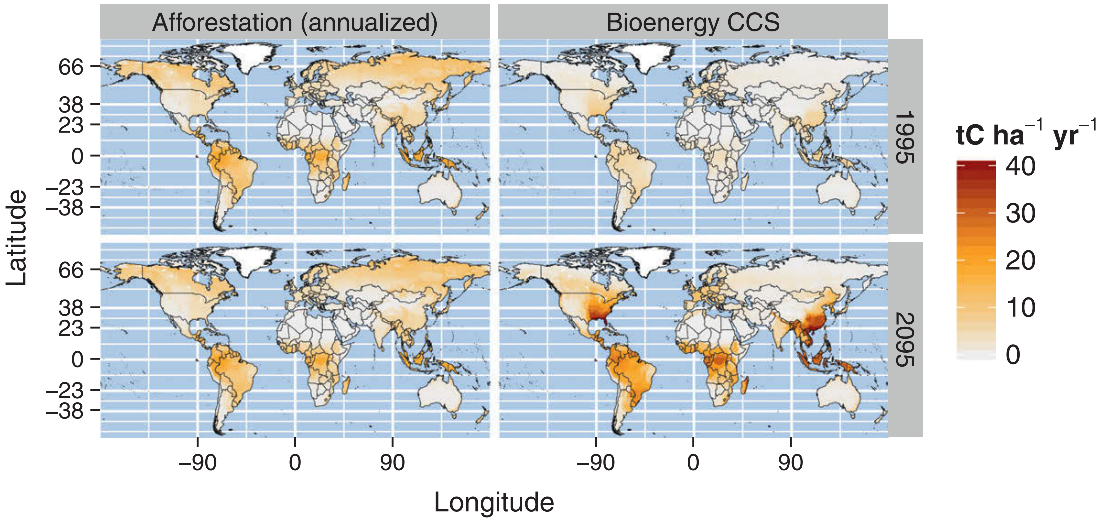

Figure 5. Grid-cell specific illustration of potential annual carbon removal rates from afforestation and bioenergy CCS for 1995 (top) and 2095 (bottom) in the AFF+BECCS scenario (tC ha^{-1} yr^{-1}). Annual carbon removal due to afforestation is calculated as average annual carbon increase in vegetation, litter and soil over a period of 30 years. Annual carbon removal due to bioenergy CCS is based on B2H2 conversion technology in combination with dedicated herbaceous bioenergy crops. Bioenergy yields are converted to carbon densities using a conversion factor of 0.45 t C/t DM. Grid-cell specific results are obtained by disaggregation of cluster level results (each grid cell is assigned the value of the cluster it belongs to).

CCS is mostly limited by the annual geological carbon injection rate. However, with a potential of 396 $GtCO_2$ yr^{-1} the constraint is not binding, which indicates that the potential of bioenergy CCS is also limited by other factors like land availability and costs associated with bioenergy production. Bioenergy production is 530 EJ yr^{-1} in HIGH, compared to 237 EJ yr^{-1} in DEFAULT and 4 EJ yr^{-1} in LOW (figure S7). In the combined setting, AFF+BECCS, land demand is similar for all parameter settings, while the difference in carbon removal is about 500 $GtCO_2$. This can be explained by considering that in the combined setting in HIGH average annual yield increases are at 1.5% yr^{-1} compared to 1.25% yr^{-1} in LOW (figure S10).

The carbon removal potential is highly sensitive to different levels of the GHG tax, which is the only driver for land-based mitigation in this study. In general, different GHG tax trajectories influence the point in time when bioenergy CCS and afforestation are cost-efficient, which translates into different mitigation potentials in 2095. While bioenergy CCS is cost-efficient starting from carbon prices of 165 \$/tCO_{2eq}, afforestation emerges as cost-efficient at prices of 6 \$/tCO_{2eq}. Therefore, the impact of changes in the GHG tax trajectory on the mitigation potential is higher in scenarios with bioenergy CCS. In AFF+BECCS, the range of sensitivity for the mitigation potential is about 900 $GtCO_2$. In general, the degree of sensitivity decreases with higher GHG tax levels, especially for afforestation.

Lower annual discount rates (4%) mostly affect the carbon removal potential of bioenergy CCS as lower discount rates facilitate long term investments in R&D translating into agricultural yield increases. On the contrary, higher discount rates (10%) increase the charges for credit, which is reflected in average annual technological change rates of 1.25% yr^{-1} in HIGH and 1.45% yr^{-1} in LOW (figure S10). The range of sensitivity for the mitigation potential is about 200 $GtCO_2$ for BECCS and 300 $GtCO_2$ for AFF +BECCS.

In terms of land, the time horizon for investment decisions mostly affects afforestation. With a time horizon of ten years, afforestation area accumulates to about 1500 mio ha, while with a time horizon of 30 or 50 years afforestation area is about 3000 mio ha, which translates into a difference in carbon removal of about 300 $GtCO_2$. The sensitivity of afforestation to the time horizon can be explained by recalling the shape of the forest growth curves in figure 3. The mitigation potential of bioenergy CCS is also affected as a shorter lifetime of investments in CCS infrastructure increases the costs associated with bioenergy CCS.

When bioenergy yields are fixed at their initial level, bioenergy CCS is less attractive as mitigation strategy. In BECCS, bioenergy production is reduced to 74 EJ yr^{-1} in LOW compared to 237 EJ yr^{-1} in DEFAULT, which results in a reduction of the mitigation potential of about 500 $GtCO_2$ until 2095. In the combined setting, AFF+BECCS, bioenergy CCS is no longer competitive with afforestation when bioenergy yield are not allowed to increase in the future, which reduces the mitigation potential in LOW compared to DEFAULT by about 300 $GtCO_2$.

The range of sensitivity across different numbers of spatial cluster units (100–500) during the optimization is small for AFF and BECCS (~50 $GtCO_2$), while it is more pronounced in the combined setting (~200 $GtCO_2$). In general, we observe a small trend towards less carbon removal with a higher number of cluster units (figure S12).

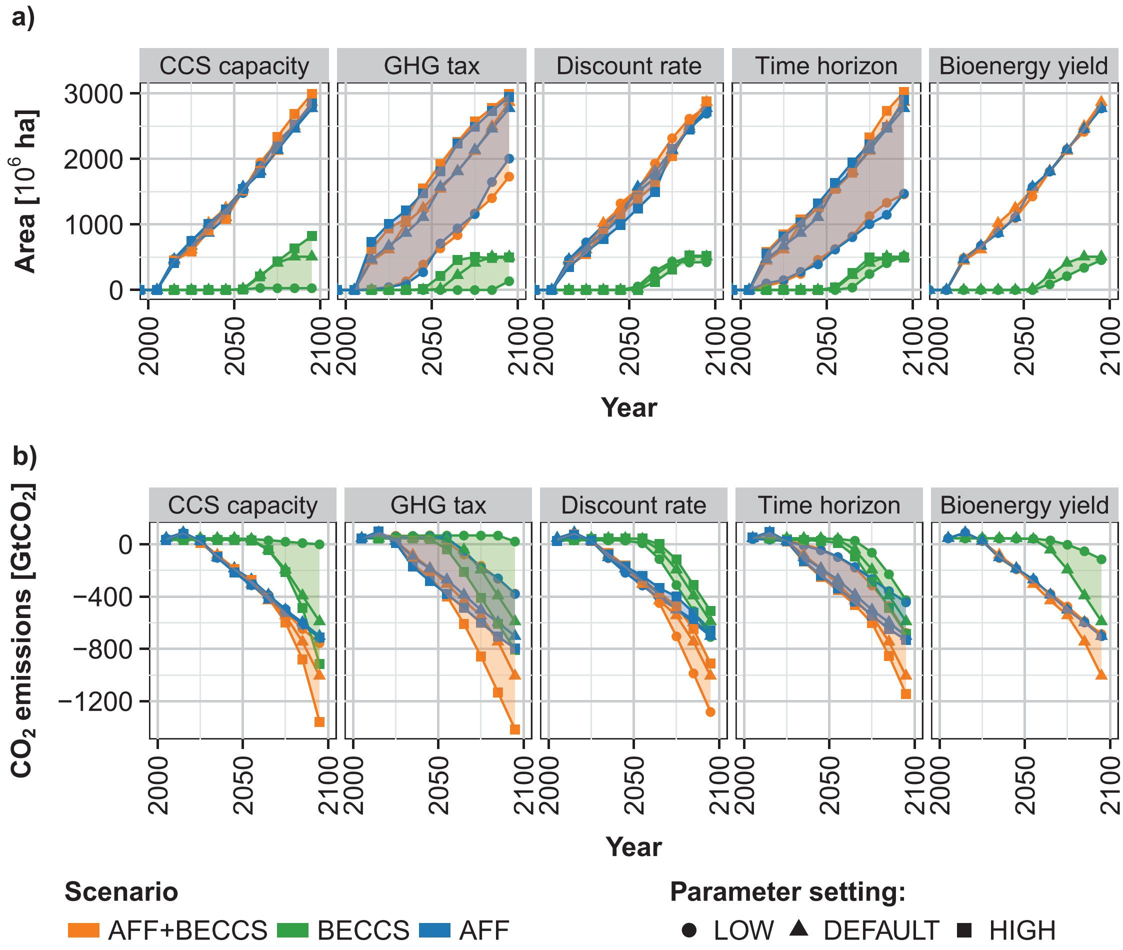

Figure 6. Time-series of sensitivity analysis for AFF, BECCS and AFF+BECCS at the global level. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, discount rate, time horizon, bioenergy yield) are described in table 3. The shaded areas span the whole range of sensitivity in the respective scenario in terms of (a) area in use for land-based mitigation (10^6 ha) and (b) cumulative CO_2 emissions ($GtCO_2$).

Discussion and conclusion

In this paper, we investigated the cumulative carbon removal potential in the land-use sector for climate change mitigation scenarios with different land-based mitigation strategies: afforestation, bioenergy CCS and the combination of both. In addition, we tested the sensitivity of our result to changes in crucial exogenous parameters.

As single mitigation strategy, afforestation is cost-efficient at relatively low carbon prices (6 $/$tCO_{2eq}$), while bioenergy CCS only becomes competitive at higher carbon prices (165 $/$tCO_{2eq}$). It should be noted that the value of energy produced via bioenergy CCS is disregarded in this study. Instead, the revenue from the GHG tax for carbon removal is considered as the only driver for bioenergy CCS and afforestation. By end-of-century, global area for land-based climate change mitigation is more than five times larger in case of afforestation (∼2800 mio ha) compared to bioenergy CSS (∼500 mio ha). For bioenergy CCS, our area estimates are comparable to recent IAM studies aiming at ambitious climate change mitigation (Popp *et al* 2014). In general, the limiting factor for land-based mitigation is the availability of land. Besides that, bioenergy production for use with CCS technology is capped by the annual realizable geological carbon injection. Therefore, bioenergy production stabilizes at 237 EJ yr^{-1} by end-of-century, which is within the range of estimated bioenergy deployment levels until 2050 (Chum *et al* 2011). Despite the dissimilarities in land demand, cumulative carbon removal by end-of-century is similar for afforestation (703 $GtCO_2$) and bioenergy CCS (591 $GtCO_2$). This can be explained by considering that, contrary to afforestation, yield-increasing technological change can enhance carbon removal per unit area of bioenergy CCS—at the expense of additional N_2O emission due to increased fertilizer use, which reduces the mitigation effect of bioenergy CCS throughout the century by about 30–50 $GtCO_{2eq}$. In addition, both options, afforestation and bioenergy CCS, benefit from area reductions in the agricultural sector due to yield increases. Based on several IAM studies, Tavoni and Socolow (2013) identify a range for cumulative carbon removal until 2100 of 200–700 $GtCO_2$ for afforestation and of 460–910 $GtCO_2$ for bioenergy CCS. Our estimates for afforestation are at the upper end of this range, while for bioenergy CCS estimates are in the middle. The combination of afforestation and bioenergy CCS leads to higher cumulative carbon removal (1000 $GtCO_2$ in AFF+BECCS) compared to scenarios with single mitigation strategies. But carbon removal in the combined setting is less than the sum of carbon removal in the standalone settings, indicating that afforestation and bioenergy CCS compete for land. Although bioenergy area is halved compared to the standalone setting, biomass production and thereby carbon removal due to bioenergy CCS is maintained—at the cost of additional yield increases. The sensitivity analysis shows that land-based mitigation is very sensitive to different levels of GHG taxes. Different GHG tax trajectories influence the point in time when bioenergy CCS and afforestation are cost-efficient, which results in different mitigation potentials in 2095. Moreover, the mitigation potential of bioenergy CCS highly depends on the development of future bioenergy yields and the availability of geological carbon storage, while for afforestation projects the length of the crediting period is crucial.

Although in 2095 the constraint on annual geological carbon injection is binding (20 $GtCO_2\,yr^{-1}$), geological carbon injection could continue for approximately another 150 years at this rate after 2095 until the cumulative carbon storage capacity is exhausted. On the other hand, carbon removal rates due to afforestation can be expected to decline when no more land for afforestation is available and forests reach maturity. Therefore, in the longer run bioenergy CCS could probably remove more carbon from the atmosphere than afforestation. Experimental model runs until 2145 support this hypothesis (figure S11). Zeng (2008), Zeng *et al* (2013) suggest an alternative carbon sequestration strategy related to afforestation. Trees could be harvested regularly and buried underground in trenches, which would prevent the decomposition of the wood for long periods (100–1000 years). Using this approach, a piece of land could be used several times for afforestation, which would probably increase the competiveness of afforestation as mitigation strategy.

Competition for land mostly takes place in the USA, China and Europe, which are attractive for both mitigation strategies. By end-of-21st-century, afforestation area is found in many world regions, especially in the tropics, while bioenergy production concentrates in the USA, China and Europe. Large-scale land-based mitigation might change the albedo of land surfaces, leading to biophysical impacts on the climate system (Vuuren *et al* 2013). Specifically in snow-covered areas of the northern hemisphere, reduction of albedo due to afforestation might jeopardize the mitigation effect of carbon removal from the atmosphere, which could result in a net warming effect (Schaeffer *et al* 2006, Bala *et al* 2007, Jackson *et al* 2008, Jones *et al* 2013). In this study, we disregard such feedbacks on the climate system. According to our results, afforestation area is found in boreal regions that might be affected by the albedo effect. However, carbon removal rates due to afforestation in these regions are low compared to the tropics, where afforestation area is found in large part.

Our results indicate that land-based mitigation primarily expands at the expense of cropland and pastureland as the conversion of forestland or other carbon-rich natural vegetation is not attractive due to the GHG tax. Moreover, timberland is not available for conversion as it is reserved for wood production (about 1270 mio ha globally). When the revenue from carbon removal due to bioenergy CCS or afforestation exceeds the revenue from forestry products, timberland might become a source of feedstock for bioenergy or part of an afforestation project. Moreover, if price-induced changes in consumption would be taken into account, competition between food production and land-based mitigation is likely to reduce food demand due to increasing prices for food production, which would result in more area available for land-based mitigation. Therefore, the area available for land-based mitigation might be underestimated in this study to the extent forestry and agricultural demand could be reduced. However, for bioenergy CCS the constraint on geological carbon injection (20 $GtCO_2\,yr^{-1}$ globally) is binding at the end of the 21st century. Hence, more available land is rather to increase carbon removal due to afforestation than due to bioenergy CCS.

In order to maintain the provision of food and feed besides land-based mitigation, yield increases in the agricultural sector would be needed to compensate for the reduction in agricultural land. In addition, the mitigation potential of bioenergy CCS relies on future increases of bioenergy yields. According to our results, land-based mitigation measures would require average annual yield increases of 1–1.38% yr^{-1} globally throughout the 21st century, which is at the lower end of historic yield increases. In the last 40 years, corn and soybean yields grew at a rate of 1.4–1.8% yr^{-1} in the USA (Egli 2008). At the global level corn yields increased by a factor of 2.5 between 1961 and 2007 (Edgerton 2009), which translates into average annual yield increases of 2% yr^{-1}. However, it is unclear if these rates of yield increase can be maintained in the future and to which extent bioenergy yields will benefit from future yield-increases in the agricultural sector. On the one hand side, measures that increase the harvestable storage organ carbon pool are specifically designed for conventional crops, while the purpose of dedicated bioenergy crops is maximum carbon accumulation across all carbon pools including stems and leaves. On the other side, conventional crops are already at high breeding levels, while breeding in bioenergy crops just started (Głowacka 2011). For instance, the estimated potential yield increase of miscanthus by 2030 is 100% (Chum *et al* 2011, p 277). In addition, also the starting point for potential bioenergy yield increases is uncertain. The range of estimates for current lignocellulosic bioenergy yields is 120–280 $GJ\,ha^{-1}$ in Europe and 150–415 $GJ\,ha^{-1}$ in South America (Chum *et al* 2011, p 234). While initial bioenergy yields in MAgPIE are at the lower end of these estimates (125 $GJ\,ha^{-1}$ in Europe, 150 $GJ\,ha^{-1}$ in Latin America; see table 1), higher initial bioenergy yields would probably render bioenergy CCS cost-efficient at lower carbon prices.

Other studies investigating bioenergy CCS and afforestation as mitigation strategies (Wise *et al* 2009, Calvin *et al* 2014, Edmonds *et al* 2013) feature a detailed representation of the energy sector. In this study, we deliberately focus on the mitigation potential of bioenergy CCS and disregard the various usage options of energy within the energy sector. Using this simplified approach, we show that bioenergy CCS could contribute to climate change mitigation in a cost-efficient way even if only the carbon removal part is valued. Another important difference concerns the assumptions about future agricultural yield increases. In other studies, yield increases follow exogenous trajectories, while investment in yield-increasing technological change in MAgPIE is a variable. Therefore, the land-use system in MAgPIE can endogenously adapt to different situations, which is for instance reflected in the amount of land used for afforestation (~2800 mio ha) compared to other studies (~1000 mio ha) (Wise *et al* 2009, Calvin *et al* 2014).

The bioenergy CCS technology is still under development and currently not applied at large economic scale (Bennaceur *et al* 2008). Furthermore, the range of estimates for geological carbon storage capacities is huge (100–200 000 $GtCO_2$) (Bradshaw *et al* 2007). Therefore, the future economic and technical feasibility of bioenergy CCS is highly uncertain. Moreover, missing social acceptance of the bioenergy CCS technology can hinder political implementation (Johnsson *et al* 2010, Knopf *et al* 2010). On the contrary, afforestation as mitigation strategy for carbon removal can be applied immediately, as it is basically planting trees. Besides that, social acceptance of afforestation is unlikely to be problematic, since forests can provide a number of ecosystem services besides carbon sequestration (e.g. water purification, biodiversity conservation, recreation) (Barlow *et al* 2007, Onaindia *et al* 2013). Valuing these ecosystem system services in addition to carbon sequestration could increase incentives for afforestation. Nevertheless, monitoring carbon stock dynamics is critical for the implementation of afforestation as mitigation strategy (Calvin *et al* 2014).

We conclude that afforestation could turn the land-use sector from a net source into a net sink of carbon before mid-century. Moreover, our results indicate that early-century afforestation presumably will not negatively impact carbon removal due to bioenergy CCS in the second half of the century. Therefore, the near-term implementation of afforestation as climate change mitigation strategy could increase the likelihood of keeping global warming below two degree above pre-industrial levels (Meinshausen *et al* 2009), while bioenergy CCS could still contribute to climate change mitigation in the second half of the century if economically, institutionally and technically feasible.

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Supplementary Information

Investigating afforestation and bioenergy CCS as climate change mitigation strategies

Florian Humpenöder, Alexander Popp, Jan Philipp Dietrich, David Klein, Hermann Lotze-Campen, Markus Bonsch, Benjamin Leon Bodirsky, Isabelle Weindl, Miodrag Stevanovic, Christoph Müller

1. Additional model description

1.1. MAgPIE regions

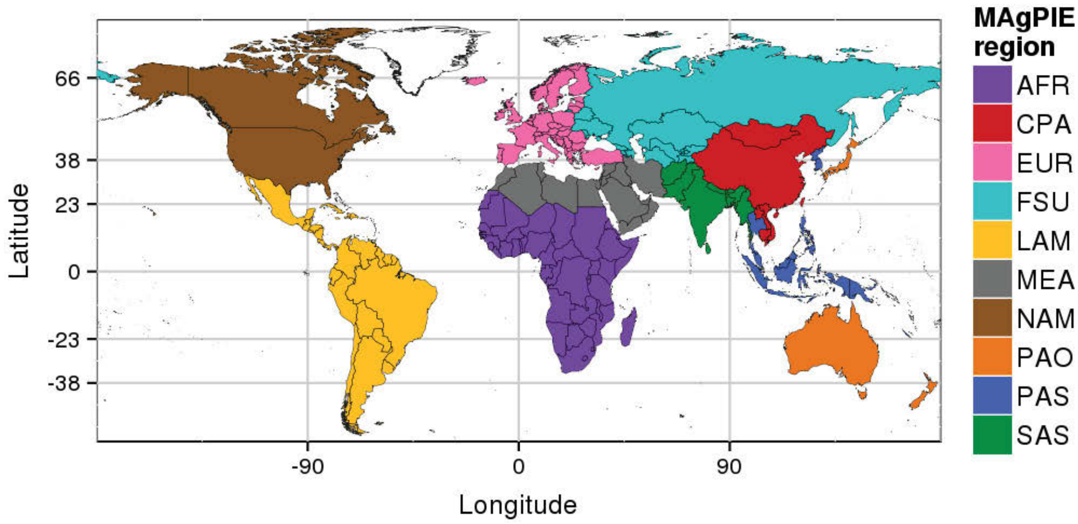

Figure S1. MAgPIE economic world regions.

MAgPIE	Region	SSP
AFR	Sub-Saharan Africa	MAF
CPA	Centrally planned Asia including China	ASIA
EUR	Europe including Turkey	OECD
FSU	States of the former Soviet Union	REF
LAM	Latin America	LAM
MEA	Middle East/North Africa	MAF
NAM	North America	OECD
PAO	Pacific OECD including Japan, Australia, New Zealand	OECD
PAS	Pacific (or Southeast) Asia	ASIA
SAS	South Asia including India	ASIA

Table S1. Abbreviations and names of the 10 economic world regions in MAgPIE, and mapping to the 5 SSP regions used in figure S8.

1.2. Demand

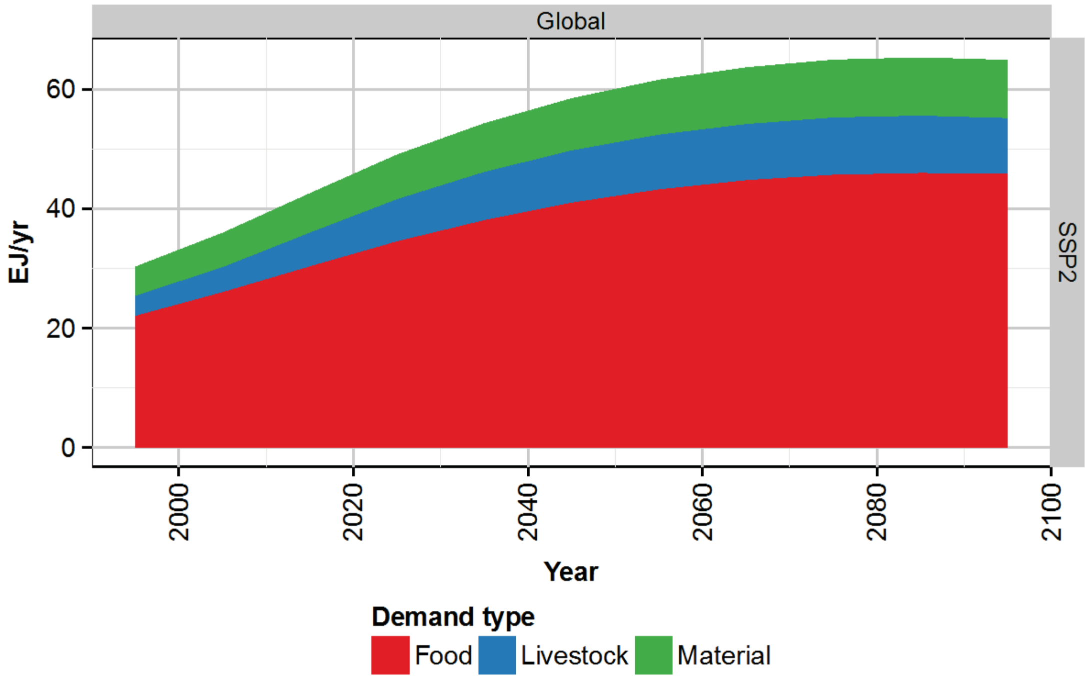

Figure S2. Time-series of food, livestock and material demand based on SSP 2 population and GDP projections (IIASA 2013).

1.3. GHG tax

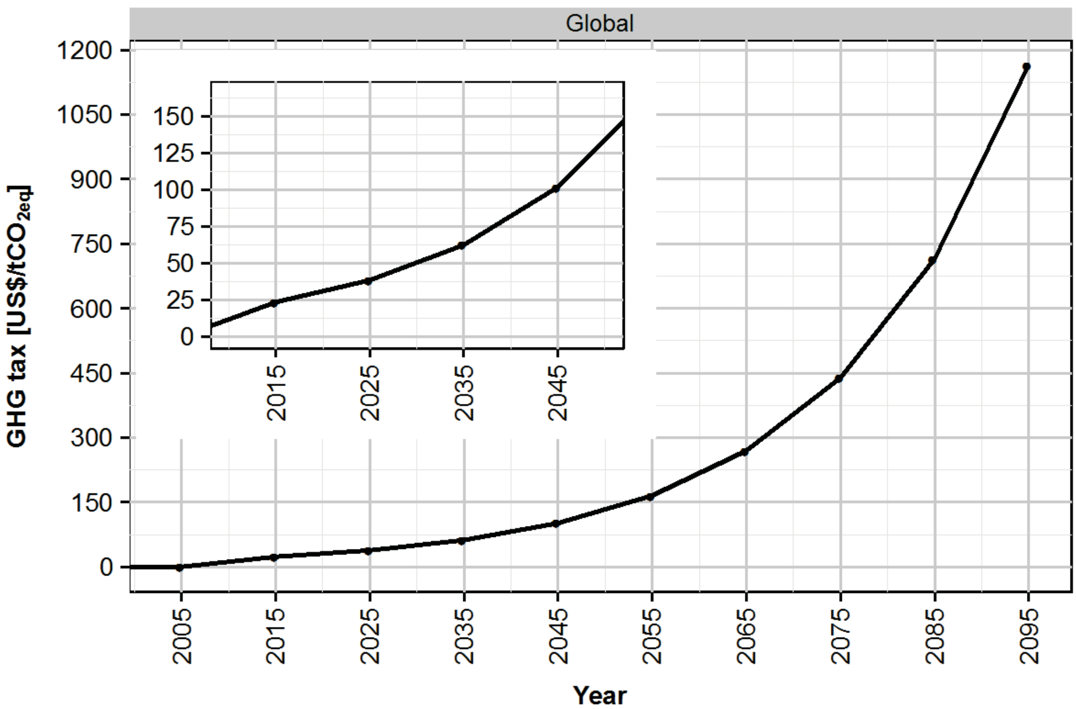

Figure S3. Time-series of assumed global tax on GHG emissions (tax30). Tax30 has a level of 30 $/tCO$_{2eq}$ in 2020, starts in 2015 and increases by 5% per year.

1.4. Afforestation costs

	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
Land conversion	863	868	1849	943	1036	987	2484	2392	968	849
Management	127	6	101	2	52	127	46	13	73	23

Table S2. Regional land conversion costs (US$/ha) and annual management costs (US$/ha/yr) in 1995, based on (Sathaye *et al* 2005).

1.5. Geological carbon storage (CCS capacity)

	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS	World
$GtCO_2$	229	367	178	917	550	458	458	367	183	183	3890
$GtCO_2$/yr	1.1	1.8	0.9	4.6	2.8	2.3	2.3	1.8	0.9	0.9	19.5

Table S3. Total regional geological carbon storage capacity ($GtCO_2$) and annual realizable injection rate ($GtCO_2$/yr). Based on Szulczewski *et al* (2012) we assume a lifetime of CCS of 200 years. Therefore, we limit the annual injection of carbon to 0.5 %/yr in terms of the total capacity. The total geological carbon storage capacity is based on Bradshaw *et al* (2007).

1.6. Regrowth of natural vegetation

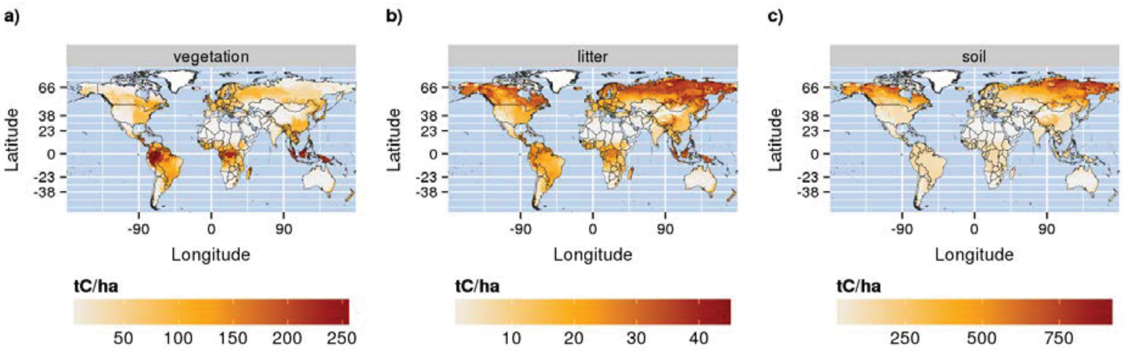

Figure S4. Grid-cell specific carbon density of potential natural vegetation in 1995 (tC/ha) derived from LPJmL for the carbon pools vegetation (a), litter (b) and soil (c). Grid-cell specific results are obtained by disaggregation of cluster level results (each grid cell is assigned the value of the cluster it belongs to).

Parameters

vegc	Age-class dependent vegetation carbon density (tC/ha)
vegc_max	Maximum vegetation carbon density (tC/ha) (Figure S4a)
k	0.075 for tropical, 0.050 for temperate, 0.033 for temperate-boreal and 0.022 for boreal climate regions. Calculated using the methodology described in Gadow and Hui (2001) and climate region specific data on Mean Annual Increment (MAI) and MAI culmination age (IPCC 2006)
m	m=3 (Murray and von Gadow 1993)
litc	Age-class dependent litter carbon density (tC/ha)
litc_max	Maximum litter carbon density (tC/ha) (Figure S4b)
soilc	Age-class dependent soil carbon density (tC/ha)
soilc_max	Maximum soil carbon density (tC/ha) (Figure S4c)
soilc_start	Soil carbon density of former land-use (tC/ha) ($soilc\_start < soilc\_max$)
c_density_ac	Age-class dependent vegetation, litter and soil carbon density (tC/ha)

Indices

j	Cluster (1-500)
ac	Age-classes (1-300)

Vegetation carbon density based on Chapman-Richards volume growth model (Murray and von Gadow 1993, Gadow and Hui 2001) (Figure 1 in manuscript):

$$vegc_{j,ac} = vegc\_max_j \times (1 - exp(-k_j \times ac))^m$$

Litter carbon density based on IPCC (2000)

$$if\ ac \leq 20: litc_{j,ac} = litc\_max_j \times 1/20 \times ac$$
$$if\ ac > 20: litc_{j,ac} = litc\_max_j$$

Soil carbon density based on IPCC (2000)

$$if\ ac \leq 20: soilc_{j,ac} = (soilc\_max_j - soilc\_start_j) \times 1/20 \times ac$$
$$if\ ac > 20: soilc_{j,ac} = soilc\_max_j - soilc\_start_j$$

Carbon density of all carbon pools

$$c\_density\_ac_{j,ac} = vegc_{j,ac} + litc_{j,ac} + soilc_{j,ac}$$

1.7. Economic incentive for land-based climate change mitigation in MAgPIE

The MAgPIE model structure is described in several publications (Lotze-Campen *et al* 2008, Popp *et al* 2010, Dietrich *et al* 2014). This section shows how the objective function of MAgPIE is modified to create an incentive for land-based climate change mitigation. The objective function has been extended for GHG emission costs, which can become negative (i.e. a cost reduction) if negative carbon emissions from afforestation or bioenergy CCS are rewarded by the GHG tax.

Variables

If not indicated otherwise, variables are defined for the range $[0, \infty]$. Variables might be subject to constraints (e.g. land).

X $[-\infty, \infty]$	Variable of the objective function (mio $/yr)
lu_costs	Total costs of land-use related activities (mio $/yr); includes all costs for the production of food, material, livestock and biomass. Considered costs types: land conversion costs, factor requirement costs (capital, labour, fertilizer), transportation costs and cost for yield-increasing technological change.
emis_costs $[-\infty, \infty]$	Total GHG emission costs (mio $/yr)
aff_costs	Total afforestation costs (mio $/yr)
beccs_costs	Total bioenergy CCS technology costs (mio $/yr)
n2o_emis	Total n2o emission (Mt N2O/yr)
ch4_emis	Total ch4 emission (Mt CH4/yr)
co2_emis $[-\infty, \infty]$	Total co2 emission (Mt CO2/yr)
c_emis_land $[-\infty, \infty]$	Total carbon emissions from the land-use system (Mt C/t)
c_emis_aff_exp $[-\infty, 0]$	Total expected carbon emissions from afforestation (Mt C/t)
c_emis_beccs $[-\infty, 0]$	Total carbon emissions from bioenergy CCS (Mt C/yr)
c_stock	Carbon stock (Mt C)
land	Total land for different land types (mio ha)
land_aff	Afforestation area (mio ha)
yield_bio	Bioenergy yield (tDM/ha/yr); can be increased due to endogenous technological change
c_removal_beccs	Carbon removal through bioenergy CCS (Mt C/yr)
bio_prod_reg	Regional biomass production (mio tDM/yr)
bio_use_reg	Regional biomass use (mio tDM/yr)
energy_costs	Total energy system costs (mio $/yr)
ccs_costs	Total CCS costs (mio $/yr)

Parameters

r	Time preference rate (7%/yr)
n	Time horizon for annualisation (30 yrs)
c_density	Carbon density for different land types (tC/ha) (based on LPJmL)
c_density_ac	Age-class dependent vegetation, litter and soil carbon density (tC/ha) for regrowth of natural vegetation (see section 1.6)
ghg_tax	Tax on GHG emissions (\$/tCO_{2eq}) (see Figure S3)
annuity	Factor for annualisation of future cash flows
lndc	Afforestation land conversion costs (\$/ha) (see section 1.4)
manc	Afforestation management costs (\$/ha/yr) (see section 1.4)
tDMtoC	Conversion factor from t DM to t C (0.45 t C/t DM)
ccs_storage_potential	Regional CCS storage potential (Mt C) (see section 1.5)
injection_rate	CCS injection rate 0.5%/yr (see section 1.5)
injection_costs	CCS injection and transportation costs (33 \$/tC)
lcoe	Levelized cost of energy for B2H2 (8 \$/GJ)
tDMtoGJ	Conversion factor from t DM to GJ (18 GJ/t DM)
conv_eff	B2H2 conversion efficiency (55%)
cap_rate	B2H2 CCS capture rate (90%)

Indices

t	Time steps (11)
i	MAgPIE world regions (10)
j	Cluster (500)
l	Land types (food, bio, past, forest, aff, other)
ac	Age-classes (300)

Sets

cell(i,j)	Mapping of regions to cluster

$$annuity = \frac{1-(1+r)^{-n}}{\frac{r}{1+r}}$$

Objective function of MAgPIE

Minimization of X_t for each t (recursive dynamic optimization)

$$X_t = lu\_costs_t + ghg\_emis\_costs_t + aff\_costs_t + beccs\_costs_t$$

Conversion to CO_{2eq} is based on GWP100 (IPCC 2013)

$$ghg\_emis\_costs_t = (n2o\_emis_t \times 265 + ch4\_emis_t \times 28 + co2\_emis_t \times 1) \times ghg\_tax_t$$

c_emis_land and c_emis_aff _exp represent carbon emissions for the whole time step length and are therefore annuitized. Conversion factor from C to CO2: 44/12.

$$co2\_emis_t = ((c\_emis\_land_t + c\_emis\_aff\_exp_t) \times \frac{1}{annuity}) + c\_emis\_beccs) \times 44/12$$

Carbon emissions are calculated as the difference of carbon stocks

$$c\_emis\_land_t = c\_stock_{t-1} - c\_stock_t$$

Carbon stocks are calculated as the product of land and carbon density

$$c\_stock_t = \sum_j \sum_l land_{t,j,l} \times c\_density_{t,j,l}$$

Calculation of carbon density for afforestation land
Constraint for afforestation land

$$land_{t,j,l="aff"} = \sum_{ac} land\_aff_{t,j,ac}$$

Simulation of forest growth by shifting age-classes according to time step length (10 yrs) between time steps (after the end of t-1 optimization and before start of t)

$$land\_aff_{t,j,ac} = land\_aff_{t-1,j,ac-10}$$

Estimate of carbon density for afforestation land pool after shifting age-classes (weighted mean)

$$c\_density_{t,j,l="aff"} = \frac{\sum_{ac} c\_density\_ac_{j,ac} \times land\_aff_{t,j,ac}}{\sum_{ac} land\_aff_{t,j,ac}}$$

Calculation of afforestation expectations and costs
Expected cumulative carbon emissions (negative) beyond the current time step (time step length = 10 yrs) but within the time horizon (n = 30 yrs), due to new afforestation area serve as incentive for the model to invest in afforestation. Emissions due to new afforestation area within the current time step are included in $c\_emis\_land_t$.

$$c\_emis\_aff\_exp_t = \sum_{j} land\_aff_{t,j,ac=0} \times (c\_density\_ac_{j,ac=10} - c\_density\_ac_{j,ac=n})$$

Regional afforestation area

$$land\_aff_{t,i,ac} = \sum_{cell(i,j)} land\_aff_{t,j,ac}$$

Afforestation costs: land conversion costs for new afforestation area, management costs for total afforestation area

$$aff\_costs_t = \sum_{i} land\_aff_{t,i,ac=0} \times lndc_i \times \frac{1}{annuity} + \sum_{i}\sum_{ac} land\_aff_{t,i,ac} \times manc_i$$

Calculation of bioenergy CCS carbon removal (negative emissions) and costs

$$c\_emis\_beccs_t = -\sum_{i} c\_removal\_beccs_{t,i}$$

Regional biomass production

$$bio\_prod\_reg_{t,i} = \sum_{cell(i,j)} land_{t,j,l="bio"} \times yield\_bio_{t,j}$$

The location of biomass use and geological carbon storage can differ from the location of biomass production

$$\sum_{i} bio\_use\_reg_{t,i} = \sum_{i} bio\_prod\_reg_{t,i}$$

Carbon removal through CCS

$$c\_removal\_beccs_{t,i} = bio\_use\_reg_{t,i} \times tDMtoC \times cap\_rate$$

CCS constraint

$$c\_removal\_beccs_{t,i} \leq ccs\_storage\_potential_i \times injection\_rate$$

Costs of bioenergy CCS

$$beccs\_costs_t = energy\_costs_t + ccs\_costs_t$$

$$energy\_costs_t = \sum_i lcoe \times bio\_use\_reg_{t,i} \times tDMtoGJ \times conv\_eff$$

$$ccs\_costs_t = \sum_i c\_removal\_beccs_{t,i} \times injection\_costs$$

2. Detailed results

2.1. Herbaceous bioenergy yields

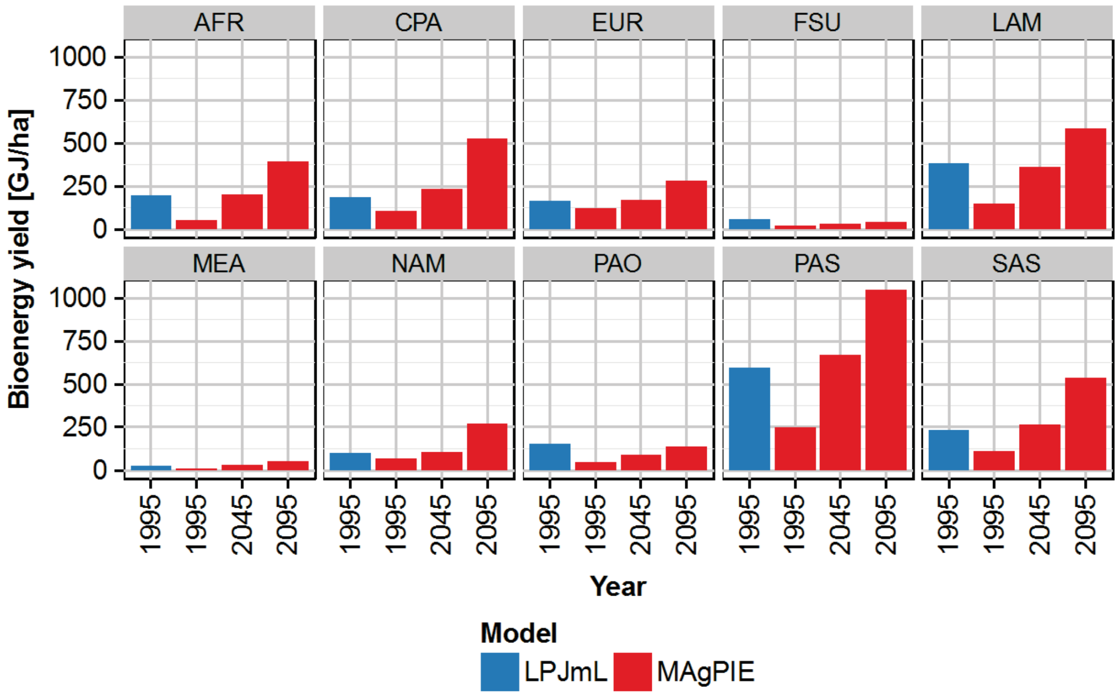

Figure S5. Regional herbaceous bioenergy yields (rain fed only) for LPJmL (1995) and MAgPIE (1995, 2045, 2095) from the AFF+BECCS scenario. LPJmL (Beringer *et al* 2011) represents potential yields, while MAgPIE aims to represent actual yields. Therefore, LPJmL yields are reduced using information about observed land-use intensity (Dietrich *et al* 2012) and agricultural area (FAO 2013). It is assumed that LPJmL bioenergy yields represent yields achieved under highest currently observed land use intensity, which is observed in EUR. Therefore, LPJmL bioenergy yields for all other regions than EUR are reduced proportional to the land use intensity in the given region. In addition, yields are calibrated at the regional level to meet FAO agricultural area in 1995, resulting in a further reduction of yields in all regions. MAgPIE bioenergy yields can exceed LPJmL bioenergy yields over time as endogenous investments in R&D push the technology frontier.

2.2. Bioenergy production

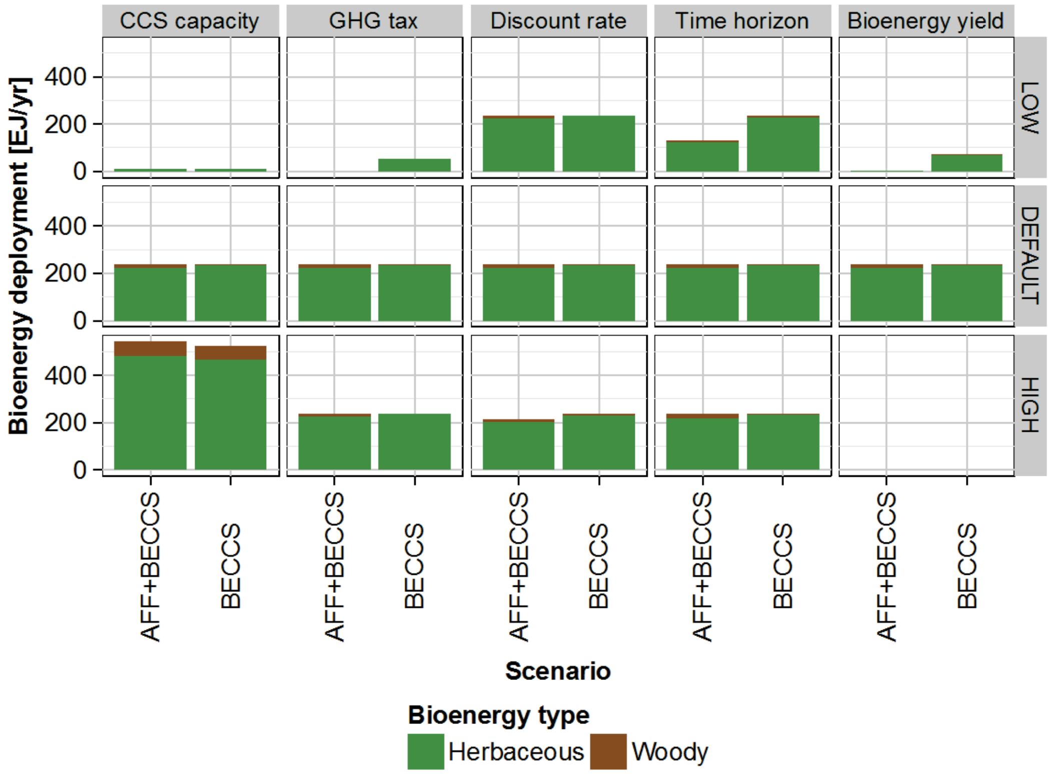

Figure S6. Sensitivity analysis of global dedicated herbaceous and woody bioenergy production (EJ/yr) for BECCS and AFF+BECCS in 2095. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, bioenergy yield) are described in table 3 of the main paper.

Figure 7. Time-series of sensitivity analysis of global bioenergy production (EJ/yr) for BECCS and AFF+BECCS. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, bioenergy yield) are described in table 3 of the main paper.

2.3. *Area in use for land-based mitigation*

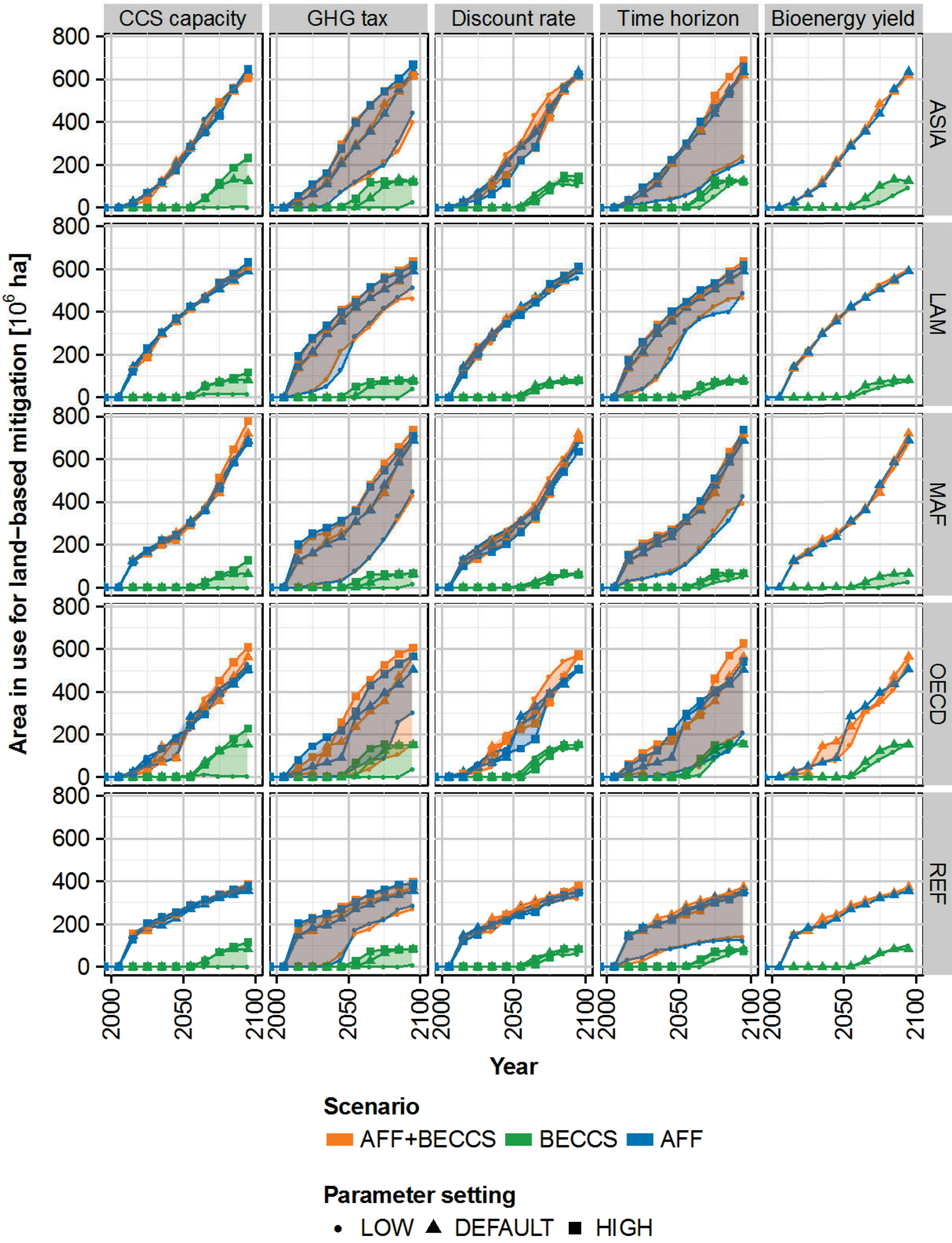

Figure S8. Time-series of sensitivity analysis of bioenergy and afforestation area for 3 scenarios at the regional level. See table S1 for mapping of regions. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, bioenergy yield) are described in table 3 of the main paper.

2.4. Cumulative non-CO_2 GHG emissions from the land-use system (N2O, CH4)

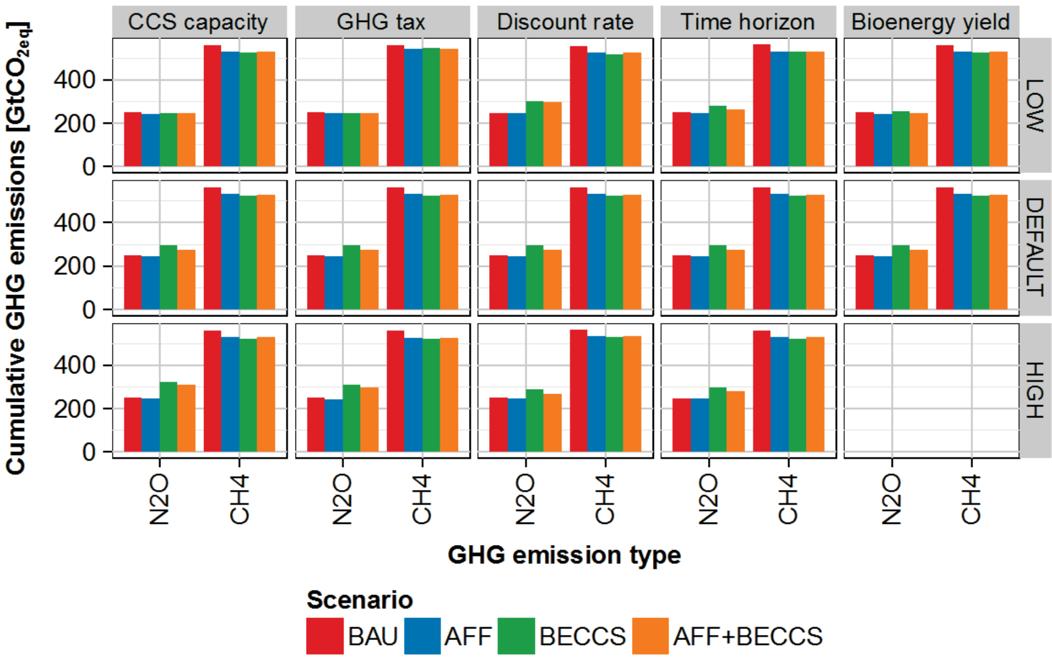

Figure S9. Sensitivity analysis of global cumulative N_2O emissions and CH_4 emissions ($GtCO_{2eq}$) in 2095 from the land-use system for 4 scenarios. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, bioenergy yield) are described in table 3 of the main paper.

2.5. Average annual yield-increasing technological change (TC)

Figure S10. Sensitivity analysis of global average annual yield-increasing technological change (TC) until 2095 for 4 scenarios. For instance, in BECCS (DEFAULT) technological change increases food and bioenergy crop yields on average by 1 %/yr, which almost triples yields within 100 years. The settings (LOW, DEFAULT, HIGH) for the different parameters (CCS capacity, GHG tax, Discount rate, Time horizon, bioenergy yield) are described in table 3 of the main paper.

2.6. Experimental model results until 2145

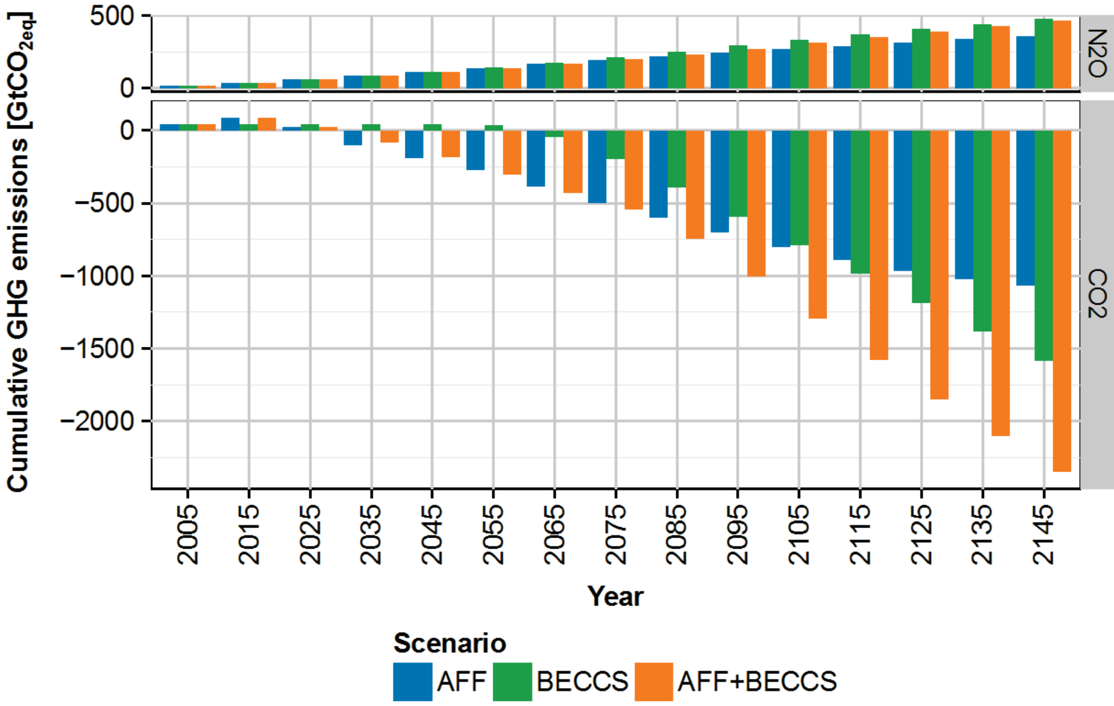

Figure S11. Time-series of global cumulative N_2O and CO_2 emissions ($GtCO_{2eq}$) from the land-use system for AFF, BECCS and AFF+BECCS until 2145. MAgPIE is parameterized to run until 2095. After 2095 we assume that food, material and livestock demand is constant on 2095 levels for this experimental model run.

2.7. Sensitivity analysis with number of cluster units

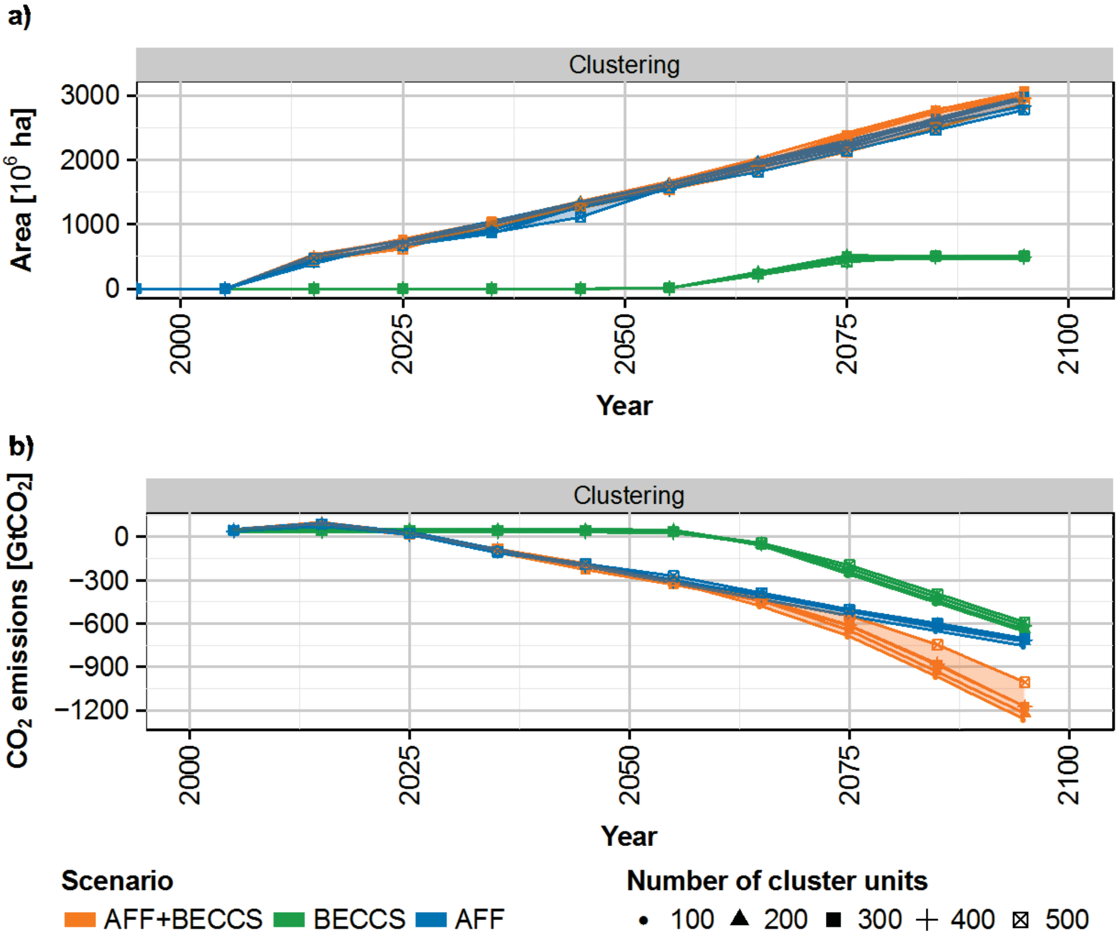

Figure S12. Time-series of sensitivity analysis for AFF, BECCS and AFF+BECCS at the global level for different numbers of cluster units. The shaded areas span the whole range of sensitivity in the respective scenario in terms of a) area in use for land-based mitigation (10^6 ha) and b) cumulative CO_2 emissions ($GtCO_2$).

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VI Land-use and carbon cycle responses to moderate climate change: implications for land-based mitigation?*

Authors:
Florian Humpenöder, Alexander Popp, Miodrag Stevanovic, Christoph Müller, Benjamin Leon Bodirsky, Markus Bonsch, Jan Philipp Dietrich, Hermann Lotze-Campen, Isabell Weindl, Anne Biewald and Susanne Rolinski

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Land-use and carbon cycle responses to moderate climate change: implications for land-based mitigation?

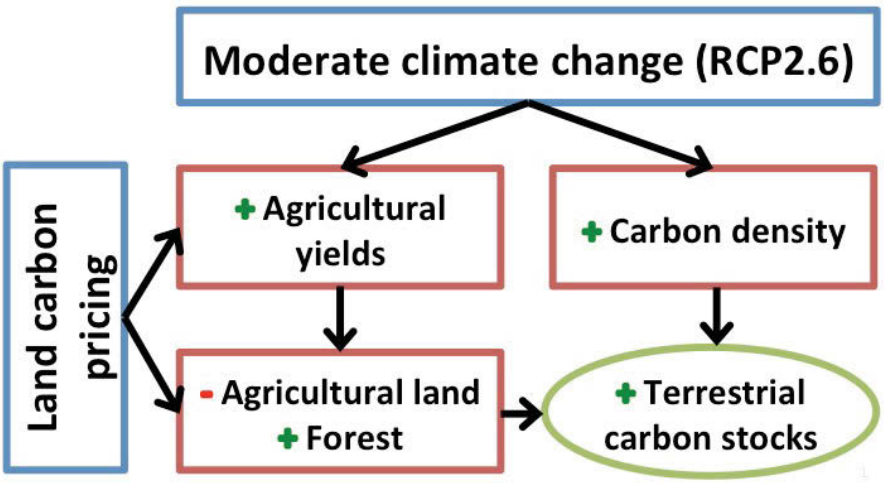
Florian Humpenöder[1,2*], Alexander Popp[1], Miodrag Stevanovic[1,2], Christoph Müller[1], Benjamin Leon Bodirsky[1,2,3], Markus Bonsch[1,2], Jan Philipp Dietrich[1], Hermann Lotze-Campen[1,4], Isabelle Weindl[1,4], Anne Biewald[1] and Susanne Rolinski[1]

[1] Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany
[2] Technische Universität Berlin (TU Berlin), Economics of Climate Change, Berlin, Germany
[3] The Commonwealth Scientific and Industrial Research Organisation (CSIRO), Brisbane, Australia
[4] Humboldt University of Berlin, Berlin, Germany

*Corresponding author: florian.humpenoeder@pik-potsdam.de

Abstract

Climate change has impacts on agricultural yields, which could alter cropland requirements and hence deforestation rates. Thus, land-use responses to climate change might influence terrestrial carbon stocks. Moreover, climate change could alter the carbon storage capacity of the terrestrial biosphere and hence the land-based mitigation potential. Here, we use a global spatially explicit economic land-use optimization model to a) estimate the mitigation potential of a climate policy that provides economic incentives for carbon stock conservation and enhancement, b) simulate land-use and carbon cycle responses to moderate climate change (RCP2.6), and c) investigate the combined effects throughout the 21st century. The climate policy immediately stops deforestation and strongly increases afforestation, resulting in a global mitigation potential of 191 GtC in 2100. Climate change increases terrestrial carbon stocks not only directly through enhanced carbon sequestration (62 GtC until 2100), but also indirectly through less deforestation due to higher crop yields (16 GtC until 2100). However, such beneficial climate impacts increase the potential of the climate policy only marginally, as the potential is already large under static climatic conditions. In the broader picture, this study highlights the importance of land-use dynamics for modelling carbon cycle responses to climate change in integrated assessment modelling.



Introduction

After fossil fuel combustion, deforestation is the second-largest source of anthropogenic carbon dioxide (CO_2) emissions, currently accounting for about 12% of total anthropogenic CO_2 emissions[1,2]. Land-based climate policies, such as the inclusion of CO_2 emissions from deforestation in carbon pricing mechanisms, could reduce deforestation and associated CO_2 emissions[3]. In addition to emission reductions, afforestation can enhance above- and belowground carbon stocks (hereafter summarized under the term *carbon stocks* unless indicated otherwise) since trees take up more CO_2 through photosynthesis than they respire and thereupon store the absorbed carbon in vegetation and soil (biological carbon sequestration and storage)[4,5]. Therefore, afforestation can remove CO_2 from the atmosphere, which is also known as negative CO_2 emissions[5,6]. Recent modelling studies show that feasibility and costs of ambitious climate targets, such as limiting the increase in global mean temperature to 2°C compared to preindustrial levels, strongly depend on the availability of carbon dioxide removal options, such as afforestation or bioenergy with Carbon Capture and Storage (CCS)[7,8].

The Representative Concentration Pathway with a radiative forcing of 2.6 W/m^2 in 2100 (RCP2.6) is consistent with the 2°C target[9–11]. Even under the RCP2.6, current climatic conditions, such as temperature and precipitation, are subject to change in the course of the 21st century[11]. Climate change is rather moderate under the RCP2.6 compared to scenarios with higher radiative forcing, such as the RCP8.5[11]. Nevertheless, moderate climate change under the RCP2.6 has impacts on agricultural crop yields[12]. Rising temperatures and reduced precipitation typically have negative impacts on crop yields, while rising atmospheric CO_2 concentrations stimulate photosynthesis in C3 crops (CO_2 fertilization) and improve water use efficiency in all crops[13–15]. The net effect on crop productivity depends on the prevailing climatic conditions[13]. Changes in temperature, precipitation, radiation and CO_2 concentration (hereafter summarized under the term *climate change* unless indicated otherwise), can have positive effects on crop yields at low levels of climate change, especially in higher latitudes, while tropical regions are typically affected negatively even under low levels of warming[12,16,17]. Increases in agricultural yields might reduce cropland requirements, which in turn could lower deforestation or free-up land for afforestation. Thus, direct effects of climate change on crop yields could indirectly affect carbon stocks through altered land management.

In addition, climate change has direct impacts on the carbon stocks of the terrestrial biosphere (in particular of forests). Similar to agricultural crops, climate change can reduce or increase carbon stocks, depending on the prevailing climatic conditions[18,19]. Biophysical process models project that climate change increases global vegetation carbon stocks throughout the 21st century[18,20]. Above 4°C additional global warming, the increase in global vegetation carbon stocks may stall or reverse[20]. Moreover, climate change affects not only actual carbon stocks but more general the carbon storage capacity of land, i.e. the potential of a unit of land to sequester and store carbon in vegetation and soil[4,21]. The carbon storage capacity plays a central role for afforestation projects since it determines their mitigation potential. Hence, climate change could influence the mitigation potential of afforestation projects. Furthermore, climate impacts on carbon stocks are heterogeneous across the globe[20]. Thus, climate change could additionally alter the spatial suitability of land for afforestation.

Projecting the direct impacts of climate change on carbon stocks of the terrestrial biosphere is typically the domain of models that simulate carbon cycle feedbacks to climate change[20,22]. However, such biophysical process models are not capable of simulating land-use responses to climate change that might indirectly alter carbon stocks (e.g. less deforestation due to climate-change-induced crop yield gains). In principle, information from biophysical process models can be used in models with explicit land-use representation to account for both, direct and indirect carbon cycle responses to climate change. So far, detailed information on climate impacts from biophysical process models has been used in economic land-use models mainly with respect to crop yields[23,24], but associated carbon stock dynamics have not been addressed. With regards to land-based mitigation, economic land-use models and integrated assessment models (IAMs) with explicit land-use representation have been used to estimate the mitigation potential of afforestation and avoidance of deforestation[3,25–27]. However, none of these studies accounted for possible land-use responses to climate change (e.g. less deforestation due to climate-change induced crop yield increases that reduce cropland requirements) and their impacts on the terrestrial carbon balance. Few studies used an inverse approach by supplying time-series of land-use patterns derived from economic land-use models to biophysical process models for simulating the effects on carbon stocks[28,29].

Here, we use the output of a biophysical process model as input for an economic land-use model to a) estimate the mitigation potential of a climate policy that provides economic incentives for carbon stock conservation and enhancement through land management, such as avoidance of deforestation and afforestation[25], b) simulate land-use and carbon cycle responses to moderate climate change (RCP2.6), and c) investigate the combined effects throughout the 21st century. First, the Lund-Potsdam-Jena model for managed Land (LPJmL)[30,31], a dynamic global crop growth and vegetation model, uses RCP2.6 climate projections as input to simulate spatio-temporal biophysical impacts on crop yields and carbon densities of natural vegetation. Subsequently, the Model of Agricultural Production and its Impacts on the Environment (MAgPIE)[25,32–34], a spatially explicit economic land-use optimization model, incorporates this biophysical information into the simulation of future land-use and carbon stock dynamics. After describing the MAgPIE model and the study design, we present the scenario results in terms of global land-use and carbon stock dynamic throughout the 21st century. Finally, we discuss the implications of our findings for future modelling of land-based climate polices and carbon cycle responses to climate change.

Methods

Land-use model MAgPIE

MAgPIE is a global economic land-use optimization model that projects spatially explicit land-use and carbon stock dynamics from 1995 to 2100[25,32–34]. The mode of optimization is recursive dynamic with a variable time step length of five or ten years. The model links high-resolution biophysical inputs with socio-economic inputs at the level of ten world regions (see Figure S1 and Table S1 in the Supporting Information (SI) for details of world regions in MAgPIE). Spatially explicit data (0.5 degree longitude/latitude) on land types (Figure S4)[35], as well as on crop yields (Figure S7) and carbon densities (Figure S5), derived from the biophysical process model LPJmL[30,31], are clustered due to computational constraints into 600 simulation units[36].

The objective function of MAgPIE is the fulfilment of agricultural demand at minimum costs under consideration of biophysical constraints, socio-economic conditions and climate polices. In the model simulations, agricultural production is associated with four cost types: factor requirement costs (labour, capital and intermediate products), land conversion costs, transportation costs and investment costs for yield-increasing technological change. MAgPIE solves the cost minimization problem through endogenous optimization of spatial production patterns, land expansion and contraction, and investments in yield-increasing technological change.

Land types in MAgPIE consist of cropland, pasture, forest and other land (e.g. non-forest natural vegetation, abandoned agricultural land, deserts, urban land). In the initial year 1995, the global land area consists of 1438 Mha cropland, 2913 Mha pasture, 4235 Mha forest and 4321 Mha other land (12907 Mha in total). We provide spatially explicit information at initialization for all land types in the SI (Figure S4). In general, all land types are free for conversion in the optimization, with the exception of urban land (1% of total land area) and 12.5% of the initial global forest area (mainly undisturbed natural forest) that lies within currently protected areas. In addition, 30% of the initial global forest area is reserved for wood production[37]. Altogether, about 86% of the world's land surface is freely available in the optimization of the initial time-step.

MAgPIE considers vegetation (living biomass), litter (dead plant material) and soil (decomposed organic matter) carbon pools. The model calculates carbon stocks at simulation unit level as the product of land type specific area and carbon density for the three carbon pools (Figure S5). If, for instance, forest is converted to cropland within the same simulation unit, the carbon stock of this unit decreases according to the difference in carbon density of forest and cropland. In case agricultural land is abandoned (other land pool) or intentionally used for afforestation (forest land pool), ecological succession leads to regrowth of natural vegetation carbon stocks along sigmoid growth curves[25].

A number of studies indicate that changes in albedo due to afforestation could counteract the associated carbon sequestration effect in high latitude regions[38–41]. In this study, we therefore prohibit afforestation in high latitude regions above 50 degree North and South.

The model is validated with respect to the historical trends in key endogenous variables in this study, i.e. cropland and pasture dynamics, land use change emissions, and crop yield increases (Figures S9 and S12-S14 in the SI).

Socio-economic setting

Our socio-economic assumptions are based on the Shared Socio-economic Pathways (SSPs) for climate change research[42]. In this study we use SSP2, which represents medium challenges for adaptation and mitigation[42]. In general, historic trends of recent decades with respect to demographics, economic development, environmental protection and technological development continue in SSP2. Food (crops and livestock) and material demand is calculated using the methodology described in *Bodirsky et al.*[43] and the SSP2 population and income projections[44]. Aggregate food and material demand increases from 30 EJ in 1995 to 65 EJ in 2100 (Figure S2).

Bioenergy

Demand for 1st and 2nd generation bioenergy is taken from the 450 FullTech REMIND/MAgPIE scenario in *Popp et al.*[45], which is consistent with a GHG stabilization target of 450 ppm CO_2 equivalent (CO_2eq) in 2100. The 450 ppm CO_2eq stabilization target corresponds to the RCP2.6, and hence to the 2°C target[9–11]. 1st generation bioenergy (food crops such as maize, sugarcane or palm-oil) peaks in 2030 at 8.5 EJ, followed by a phase-out until 2050 (Figure S2). 2nd generation bioenergy demand (lignocellulosic biomass such as miscanthus or poplar) is projected to strongly increase from 7 EJ in 2030 to 236 EJ in 2060, followed by a slight decline to 229 EJ until 2100 (Figure S2). In the 450 ppm climate policy scenarios, a large share of 2nd generation bioenergy is used in combination with CCS for generating negative CO_2 emissions in the energy sector[45,46]. We here cover CO_2 emissions due to bioenergy crop production in the land-use sector, but do not account for emissions or emission savings due to bioenergy use in other sectors.

Climate policy

In this study, Land Carbon Pricing (LCP) represents a climate policy that prices all carbon stock changes that originate from anthropogenic land-use change. For this purpose, the product of released CO_2 to the atmosphere (tCO_2) and a price on CO_2 emissions ($\$/tCO_2$) enters the cost-minimizing objective function of the model as additional term on top of agricultural production cost. Thus, LCP provides economic incentives for carbon stock conservation through endogenous avoidance of land conversions that are associated with high carbon losses, such as deforestation. For carbon stock gains, which reflect negative CO_2 emissions, this additional term in the objective function becomes negative. Accordingly, LCP provides also economic incentives for land management that enhances carbon stocks, such as afforestation. We use a global uniform carbon price trajectory, which starts at 24 $\$/tCO_2$ in 2015 and increases non-linearly at a rate of 5% per year, reaching 130 $\$/tCO_2$ in 2050 and 1487 $\$/tCO_2$ in 2100 (Figure S3). This carbon price trajectory, taken from the energy-economy-climate model REMIND (REgional Model of Investments and Development), is close to the carbon prices projected for a GHG stabilization target of 450 ppm CO_2eq in 2100[47]. Other assessment models report similar carbon prices for such ambitious climate targets[10,27].

Climate impacts

General Circulation Models (GCMs) compute changes in climate variables, such as temperature and precipitation, for a given RCP. To account for uncertainty in climate projections, we use climate projections from five different GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M) that have been bias-corrected for the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP)[48]. Consistent with bioenergy demand and carbon prices (see above), we here use climate projections for the RCP2.6. We implicitly assume that all mitigation efforts to meet the RCP2.6 emissions trajectory that are needed beyond bioenergy deployment and land-based carbon mitigation take place outside the land-use sector, e.g. in the energy, transport or building sector. The dynamic global crop growth, vegetation and hydrology model LPJmL[29,31] uses RCP2.6 climate projections as input to simulate spatio-temporal biophysical impacts on crop yields (Figure S8), carbon densities of natural vegetation (Figure S6) and surface freshwater availability. In the model simulations, LPJmL considers the impact of temperature, precipitation, radiation and CO_2 concentration. Elevated CO_2 concentrations enhance plant photosynthesis in C3 plants, which is known as CO_2 fertilization, and simultaneously increases water use efficiency in all plants[14,15]. There is indication that the current generation of biophysical process models overestimates CO_2 fertilization due to missing feedback representations in photosynthetic activity[49,50]. The current version of LPJmL does not explicitly represent nutrient dynamics and might therefore overestimate CO_2 fertilization[31]. After harmonization of LPJmL-based crop yields and carbon densities for the initial MAgPIE time step (see SI for details), MAgPIE incorporates this biophysical information into the simulation of future land-use dynamics and associated carbon stock changes.

Study setup

In order to investigate if land-use and carbon cycle responses to RCP2.6 climate impacts interact with a land-based climate policy throughout the 21st century, we analyse the isolated and combined effects of a LCP climate policy and RCP2.6 climate impacts with the MAgPIE model. For this purpose, we define reference cases for the LCP climate policy and the RCP2.6 climate impacts. In NoLCP, carbon stock changes are not priced, i.e. there is no incentive for afforestation or avoidance of deforestation. In NoCC (No Climate Change), biophysical crop yields and carbon densities are assumed to be static at 1995 levels throughout the simulation period. The combinations of the two climate policy cases (LCP / NoLCP) and the two climate impact cases (RCP2.6 / NoCC) result in four scenarios: *reference* (NoLCP & NoCC), *LCP only* (LCP & NoCC), *RCP2.6 only* (NoLCP & RCP2.6) and the *combined setting* (LCP &

RCP2.6). To account for uncertainty in climate projections, all scenarios with climate impacts are simulated with RCP2.6 biophysical climate impact projections from LPJmL that are based on climate projections from five different GCMs. Table 1 summarizes the study design.

Table 1: Summary of study design

Socio-economic setting, bioenergy demand and carbon prices
The economic land-use optimization model MAgPIE is parameterized with a socio-economic setting for the 21st century based on SSP2 (e.g. population, income, food demand). 1st and 2nd generation bioenergy demand as well as carbon prices are consistent with a GHG stabilization target of 450 ppm CO_2eq in 2100, which corresponds to the RCP2.6.
Land-based climate policy
Land Carbon Pricing (LCP) involves pricing of all carbon stock changes that originate from anthropogenic land-use change. LCP provides economic incentives for carbon stock conservation and enhancement through land management, such as avoidance of deforestation and afforestation. NoLCP represents a reference case, in which carbon stock changes are not priced.
Climate impacts on the land system
Consistent with bioenergy demand and carbon prices, we here use RCP2.6 climate projections. The biophysical process model LPJmL derives impacts on crop yields and carbon densities of natural vegetation for RCP2.6 climate projections from five different GCMs. The economic land-use optimization model MAgPIE incorporates this output of LPJmL into the simulation of future land-use dynamics and associated carbon stock changes. NoCC represents a reference case, in which biophysical crop yields and carbon densities are assumed to be static at 1995 levels.
Study setup
The combinations of the two climate policy cases (LCP / NoLCP) and the two climate impact cases (RCP2.6 / NoCC) result in four scenarios: *reference* (NoLCP & NoCC), *LCP only* (LCP & NoCC), *RCP2.6 only* (NoLCP & RCP2.6) and the *combined setting* (LCP & RCP2.6).

Results

Across all scenarios global land-use changes range from about -1500 Mha for pastureland to +1700 Mha for forestland by 2100 (Figure 1), associated with global carbon stock changes ranging from about -100 GtC to +200 GtC by 2100 (Figure 2). We report land-use and carbon stock changes for scenarios with RCP2.6 climate impacts as average over the five GCM-specific RCP2.6 climate projections, while the respective Figures 1 and 2 show the full range of results. In the SI, we show regional results in Figure S10 and Figure S11, and provide GCM-specific results at the global scale in Table S2 and Table S3 (land-use and carbon stock dynamics respectively).

Reference scenario

In the *reference* scenario (NoLCP & NoCC), global cropland increases by 698 Mha between 1995 and 2100 (Figure 1, left, dashed lines), which reflects a strong rise in 2nd generation bioenergy demand between 2030 and 2060 (Figure S2). The increase in cropland mainly comes at the cost of forest area, which decreases by 511 Mha in the same period. The remaining cropland increase of 187 Mha originates from the conversion of pastureland. In addition, 1025 Mha of pastureland are abandoned until 2100 (other land) due to efficiency improvements in the livestock sector and stagnating demand for livestock products in the 2nd half of the 21st century (Figure S2). In order to fulfil the agricultural demand, land-use intensification and changes in spatial production patterns complement agricultural expansion. In the *reference* scenario, global average agricultural yields increase from 3.1 tDM ha^{-1} in 2005 to 5.0 tDM ha^{-1} in 2100, which reflects average yield increases of about 0.5% per year until 2100. Simulated agricultural yields in 2005 as well as the historical trend of yield-growth compare well to observed data on agricultural yields at the global scale (Figure S9).

The net effect of these land-use changes in the *reference* scenario is a loss of global terrestrial carbon of 90 GtC until 2100 (Figure 2, left, dashed lines; Table 2). Loss of terrestrial carbon largely coincides with deforestation, in particular between 2030 and 2060. In the *reference* scenario, carbon stocks are assumed to be unaffected by climate change (NoCC).

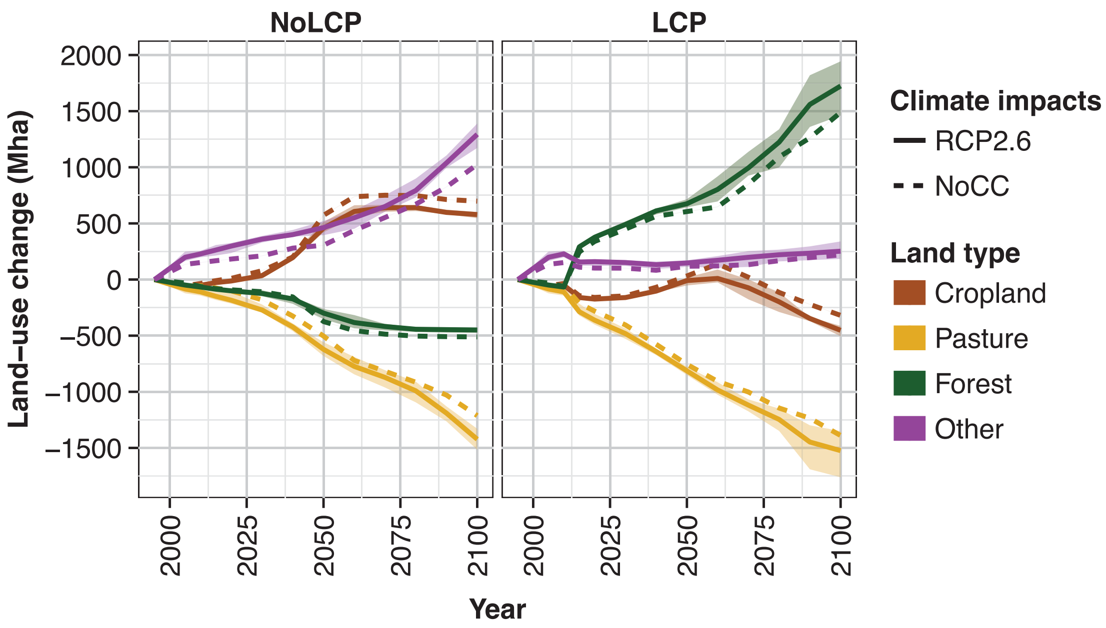


Figure 1: Time-series of global land-use change (Mha) for four major land types between 1995 and 2100. The combinations of climate policy (*NoLCP*, *LCP*; left vs. right column) and climate impacts (*RCP2.6*, *NoCC*; solid vs. dashed lines) result in four scenarios. Solid lines represent the average over individual model results for five GCM-specific RCP2.6 climate projections, while shaded areas indicate the full range of results.

Land-based climate policy

In the *LCP only* scenario (LCP & NoCC), carbon prices create a strong incentive to conserve and enhance carbon stocks (Figure 1, right, dashed lines). The introduction of the global carbon price in 2015 at 24 \$/tCO_2 immediately stops deforestation and strongly increases afforestation. In total, global forest area increases by 1489 Mha throughout the 21st century, which results in 2000 Mha more forest in 2100 compared to the *reference* scenario. About half of the increase in forest area is realized by cropland contraction. Global cropland area decreases in total by 319 Mha throughout the 21st century, which results in 1018 Mha less cropland in 2100 compared to the *reference* scenario. To facilitate such strong cropland contraction, agricultural yields have to rise much stronger throughout the 21st century than in the *reference* scenario. In *LCP only*, global average agricultural yields increase from 3.1 tDM ha^{-1} in 2005 to 11.2 tDM ha^{-1} in 2100, which reflects average annual yield increases until 2100 of about 1.36%, compared to 0.5% in the *reference* scenario (Figure S9). The remaining increase in forest area originates from abandoned pasture area. Pasture area decreases by 1390 Mha throughout the 21st century, which is similar to pasture contraction in the *reference* scenario (1212 Mha until 2100). But in contrast to the *reference* scenario, converted pastureland is primarily used for afforestation in *LCP only*, while just 220 Mha of converted pastureland are abandoned (other land). On-going afforestation throughout the 21st century in *LCP only* increases global carbon stocks by 101 GtC until 2100 (Figure 2, right, dashed lines; Table 2). In addition, deforestation and other conversions of carbon-rich ecosystems that occur in the *reference* scenario are stopped. Therefore, the global mitigation potential attributable to a land-based climate policy that provides economic incentives for carbon stock conservation and enhancement is 191 GtC between 1995 and 2100. As in the *reference* scenario, carbon stocks are assumed to be not affected by climate change (NoCC) in *LCP only*.

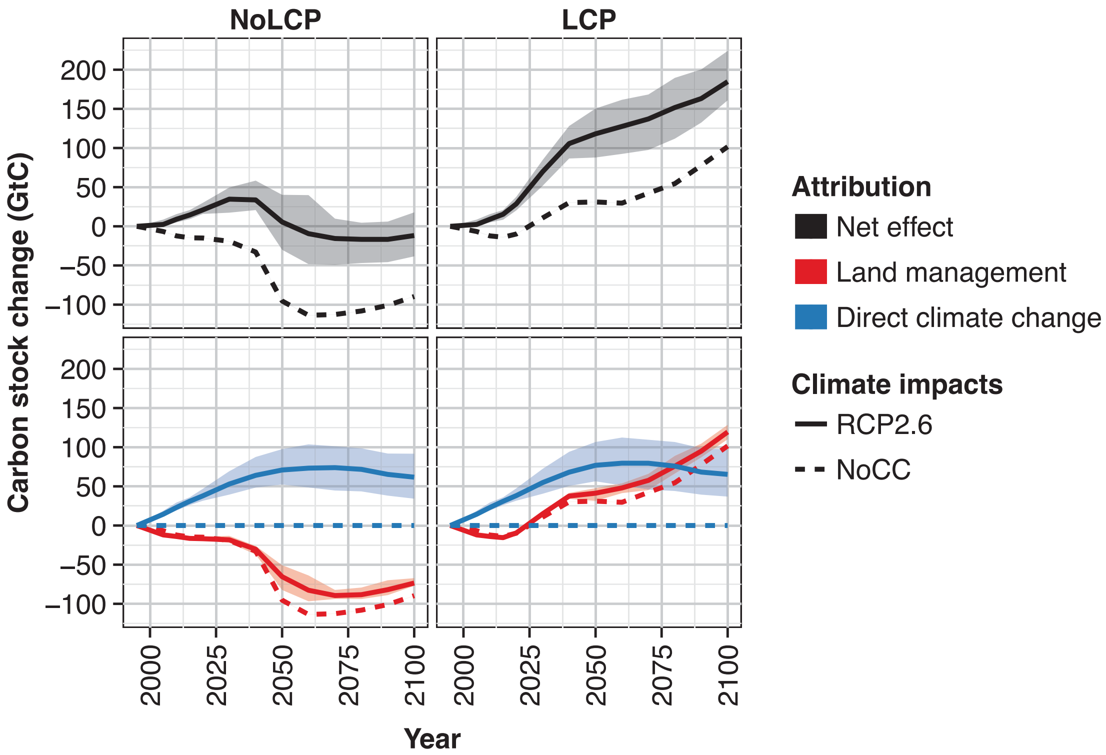


Figure 2: Time-series of global terrestrial carbon stock change (GtC) between 1995 and 2100. The combinations of climate policy (*NoLCP*, *LCP*; left vs. right column) and climate impacts (*RCP2.6*, *NoCC*; solid vs. dashed lines) result in four scenarios. Colours indicate the attribution of changes in carbon stocks. *Land management* reflects carbon stock changes associated with the land-use dynamics shown in Figure 1 and includes indirect effects of climate change on carbon stocks through altered land management. *Direct climate change* reflects carbon stock changes due to direct impacts of climate change on carbon sequestration in the terrestrial biosphere. The *net effect* on carbon stocks is represented by the sum of *land management* and *direct climate change*. Solid lines represent the average over individual model results for five GCM-specific RCP2.6 climate projections, while shaded areas indicate the full range of results.

RCP2.6 climate impacts

In general, land-use dynamics under static climatic conditions (NoCC) and moderate climate change (RCP2.6) are similar throughout the 21st century (Figure 1, left, solid vs. dashed lines). However, in the *RCP2.6 only* scenario (NoLCP & RCP2.6) global agricultural area (cropland and pasture) is 330 Mha smaller in 2100 compared to the *reference* scenario with static climatic conditions. The reduced land requirement for agriculture translates until 2100 into 62 Mha more forest (less deforestation) and 268 Mha more other land with potentially re-growing natural vegetation. This land-saving effect originates from the land-use response to higher agricultural yields under RCP2.6 climate projections: global average agricultural yields are 0.3 tDM ha^{-1} higher in 2100 compared to the *reference* scenario (Figure S9).

Altered land management in *RCP2.6 only* results in 16 GtC higher global carbon stocks in 2100 compared to the *reference* scenario (Figure 2, left, solid vs. dashed lines). In addition to this indirect effect via land management, climate change has direct impacts on the carbon stocks of the terrestrial biosphere through altered plant photosynthesis and respiration. Due to direct impacts of climate change, global carbon stocks in *RCP2.6 only* are 62 GtC higher in 2100 compared to the *reference* scenario. The overall global carbon stock dynamics in *RCP2.6 only* follow the trajectory of the atmospheric CO_2 concentration for RCP2.6 climate projections: increase until mid-21st century followed by a smaller decrease until 2100[10]. In total, global carbon stocks in *RCP2.6 only* are 78 GtC higher in 2100 compared to the *reference* scenario, which shows carbon losses of 90 GtC until 2100. Therefore, in absolute terms global carbon stocks still decrease by 12 GtC until 2100 in *RCP2.6 only*.

Overall, the uncertainties in land-use dynamics (Figure 1), carbon stock dynamics (Figure 2) and agricultural yields (Figure S9), which are introduced by the five GCM-specific RCP2.6 climate projections, do not change our results qualitatively.

Table 2: Summary of scenario results. Carbon stock changes and full carbon mitigation effect in GtC. Carbon stock changes show the net effect of land management and direct climate change between 1995 and 2100 at the global scale (Figure 2). The full carbon mitigation effect reflects the difference in these carbon stock changes between the respective scenario and the *reference* scenario. To identify the interaction between a LCP climate policy and RCP2.6 climate impacts, we compare the sum of the full mitigation effects of the *LCP only* (191 GtC) and the *RCP2.6 only* scenario (78 GtC) to the full mitigation effect of the *combined setting* (275 GtC). The small difference of 6 GtC suggests that the interaction between a LCP climate policy and RCP2.6 climate impacts is low. This table shows average values over five GCM-specific RCP2.6 climate projections.

	NoLCP		LCP	
NoCC	*Reference*		*LCP only*	
	Δ Carbon stock	Full effect	Δ Carbon stock	Full effect
	-90 GtC	0 GtC	101 GtC	191 GtC
RCP2.6	*RCP2.6 only*		*Combined setting*	
	Δ Carbon stock	Full effect	Δ Carbon stock	Full effect
	-12 GtC	78 GtC	185 GtC	275 GtC

191 GtC + 78 GtC = 269 GtC ~ 275 GtC

Combined effects

In the *combined setting* of a LCP climate policy and RCP2.6 climate impacts (LCP & RCP2.6), overall land-use dynamics are similar to *LCP only* (Figure 1, right, solid vs. dashed lines). In the *combined setting*, however, agricultural land requirements are 267 Mha lower in 2100, which is similar to the identified land-saving effect for *RCP2.6 only* (330 Mha in 2100). Contrary to *RCP2.6 only*, most of the agricultural land released by the land-saving effect is immediately used for afforestation in the *combined setting* (235 Mha until 2100). Regrowth of natural vegetation with associated carbon stock gains takes place regardless of the allocation to forest or other land sine afforestation is a managed re-growth of natural vegetation in the MAgPIE model[25]. Accordingly, the climate-change-induced gain in global carbon stocks due to land management is similar to *RCP2.6 only* (Figure 2, left vs. right, solid vs. dashed lines). Also the increase in global carbon stocks due to direct impacts of climate change is similar to *RCP2.6 only*. Thus, RCP2.6 climate impacts seem to increase global carbon stocks independent from a LCP climate policy.

In the *combined setting*, the net effect of land management and climate change is an increase of global carbon stocks by 185 GtC until 2100 (Figure 2, right, solid lines; Table 2). Since global carbon stocks decrease by 90 GtC until 2100 in the *reference* scenario, the full cumulative carbon mitigation effect in 2100 attributable to the *combined setting* is 275 GtC. This full effect is 191 GtC for *LCP only* and 78 GtC for *RCP2.6 only*. The sum of these isolated effects is 269 GtC in 2100. Thus, the additional carbon stock gain that emerges from the *combined setting* is 6 GtC throughout the 21st century (Table 2). If this gain is completely accounted to the mitigation potential of the *LCP only* scenario (191 GtC in 2100), the mitigation potential increases by just 3%. Therefore, land-use and carbon cycle responses to RCP2.6 climate impacts only marginally affect the mitigation potential that can be attributed to a land-based climate policy in the 21st century.

Discussion

Land-based climate policy

We find that the introduction of a carbon price in the land-use sector immediately stops deforestation and strongly increases afforestation throughout the 21st century. While the carbon prices used in this study are close to projected carbon prices for ambitious climate targets, *Humpenöder et al.*[25] show that afforestation is a cost-efficient mitigation option even at substantially lower carbon prices starting from 6 $/t$CO_2$. According to our results, current global forest area increases by about one third until 2100, associated with carbon stock gains of 101 GtC globally until 2100. A reference scenario without carbon pricing shows carbon losses of 90 GtC until 2100, mainly due to deforestation. Therefore, the cumulative mitigation potential attributed to the land-based climate policy analysed in this study is 191 GtC throughout the 21st century. Global forest area mainly increases at the cost of agricultural land, which could only be realized by considerable productivity increases in the agricultural sector (see also *Humpenöder et al.*[25]). The competition for land between the production of agricultural commodities and afforestation might more than double food prices throughout the 21st century[26,51]. This gives reason to consider food security implications of land-based climate policies, such as the United Nations' REDD+ (*reducing emissions from deforestation and forest degradation)* mechanism, which aims to provide economic incentives for afforestation and avoidance of deforestation[52,53]. Keeping food consumption levels unaffected from such land-based climate policies, as we did for these model runs, would require substantial redistribution policies to assure food security for low-income households (see also *Edmonds et al.*[27]). Analysis of the economic aspects of food security is critical for the implementation of land-based climate policies, but beyond the scope of this study.

Land-use and carbon cycle responses to RCP2.6 climate impacts

We find that accounting for RCP2.6 climate impacts in an economic land-use model increases global carbon stocks by 78 GtC until 2100, compared to a reference scenario with static climatic conditions. Enhanced carbon sequestration of the terrestrial biosphere under RCP2.6 causes the major part of this difference (62 GtC in 2100). However, 21% of the total climate-change-induced carbon stock gains originate from a land-saving effect due to higher agricultural yields under RCP2.6 (16 GtC in 2100). This finding highlights the importance of land-use dynamics for modelling carbon cycle responses to climate change

As already noted in the methods part, LPJmL estimates of CO_2 fertilization on crop yields are more positive than in many other global crop models[12]. Therefore, the projected gains in carbon stocks due to RCP2.6 climate impacts might be overestimated. On the other hand, atmospheric CO_2 concentrations in the RCP2.6 return to current levels in 2100 (383-385 ppm) after a peak caused by exceeding the climate target around mid-century ("overshooting")[9,10]. Thus, the choice of the RCP2.6 should limit the overall magnitude of CO_2 fertilization and associated nutrient demand. If the impacts of climate change on agricultural yields are negative, which is likely the case for local temperature increases above 3°C[16,17] or in the warm tropics[12], land-use and carbon stock dynamics could reverse: lower agricultural yields might increase cropland requirements, causing more deforestation or hampering ecological succession.

Why RCP2.6 climate impacts hardly affect a land-based climate policy

In this study, we project a) that the global mitigation potential of a land-based climate policy is 191 GtC in 2100, and b) that carbon stock gains due to RCP2.6 climate impacts cumulate to 78 GtC until 2100. The sum of these isolated effects (269 GtC) is just slightly lower than the actual result for the combined setting in 2100 (275 GtC), which suggests that moderate climate change in the 21st century only marginally affects the mitigation potential that can be attributed to the land-based climate policy.

There are two reasons for this loose link between RCP2.6 climate impacts and a land-based climate policy. First, carbon prices create a strong incentive for afforestation and avoidance of deforestation already under static climatic conditions. Hence, beneficial impacts of climate change on crop yields and carbon storage capacity, as we project in this study for the RCP2.6, do not substantially increase the mitigation potential attributable to a land-based climate policy. Second, afforestation projects typically last for 20-60 years[54]. Over such long periods, climate change might alter the carbon sequestration in forests[20]. Thus, owing to its long-term character, the mitigation potential of afforestation projects could increase or decrease due to climate change. In particular, negative impacts on the outcome of afforestation projects are critical. If negative climate impacts would offset re-growth of carbon stocks in future time steps, stopping an afforestation project and using the land for other purposes is only a limited option since a clear-cutting of the already existing forest comes with costs for the associated CO_2 emissions. Therefore, afforestation projects introduce a path dependency for land-use, which prevents abrupt changes in land-use due to climate change.

Implications for future modelling

In general, our results stress that land-use responses to climate change should be considered in simulations of carbon cycle feedbacks to climate change. This could be of particular importance for IAMs, which are typically used for estimating mitigation efforts and costs across economic sectors for a specific climate target[10]. Currently, several IAMs use the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC) to account for the feedbacks between the carbon cycle and the climate system[10]. MAGICC simulates simplified CO_2 fertilization and temperature feedbacks on the terrestrial biosphere without consideration of land-use dynamics[10,22]. Accordingly, carbon stock changes that result from land-use responses to climate change are disregarded. For instance, our results suggest global carbon stocks gains of 16 GtC until 2100 due to land-saving effects under RCP2.6. Depending on potential carbon prices of several hundred dollars by 2100, as projected by several IAMs[7,9,10], the net present value of these 16 GtC could be huge. A more sophisticated representation of the interactions between climate, terrestrial biosphere and anthropogenic land-use dynamics with respect to carbon stocks could therefore play a vital role for improving estimates of mitigation efforts and costs in IAMs.

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Supporting Information (SI)

Additional model description and detailed results.

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Supplementary Information (SI)

Land-use and carbon cycle responses to moderate climate change: implications for land-based mitigation?

by Florian Humpenöder, Alexander Popp, Miodrag Stevanovic, Christoph Müller, Benjamin Leon Bodirsky, Markus Bonsch, Jan Philipp Dietrich, Hermann Lotze-Campen, Isabelle Weindl, Anne Biewald and Susanne Rolinski

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1. Additional model description

1.1. Model version

All simulations for the scenario analysis in this study have been carried out with the Model of Agricultural Production and its Impacts on the Environment (MAgPIE)[1–4], revision 7753.

1.2. Model regions

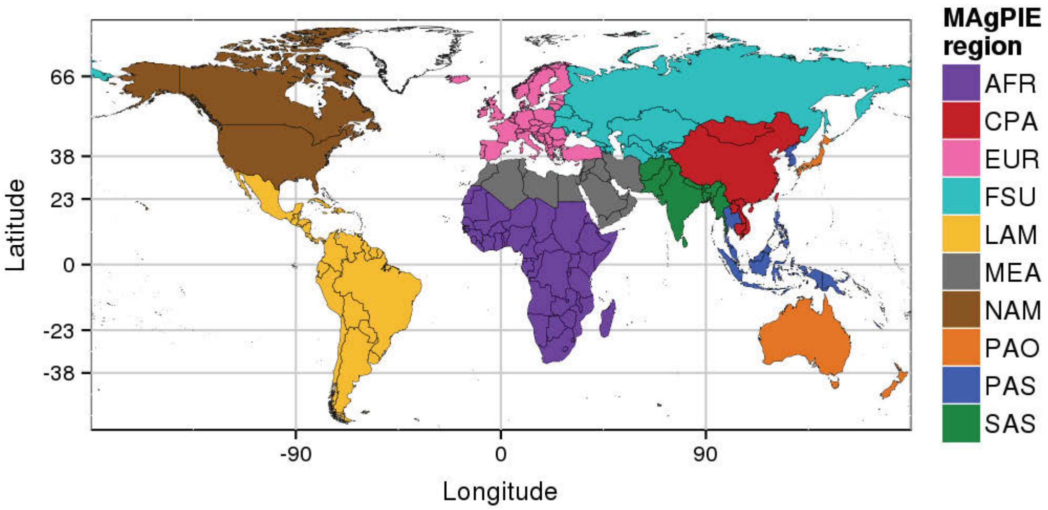

Figure S1: MAgPIE economic world regions.

MAgPIE	Region	SSP
AFR	Sub-Saharan Africa	MAF
CPA	Centrally planned Asia including China	ASIA
EUR	Europe including Turkey	OECD
FSU	States of the former Soviet Union	NOLCP
LAM	Latin America	LAM
MEA	Middle East/North Africa	MAF
NAM	North America	OECD
PAO	Pacific OECD including Japan, Australia, New Zealand	OECD
PAS	Pacific (or Southeast) Asia	ASIA
SAS	South Asia including India	ASIA

Table S1: Abbreviations and names of the 10 economic world regions in MAgPIE, and mapping to the 5 SSP regions used in Figure S10 and Figure S11.

1.3. Demand

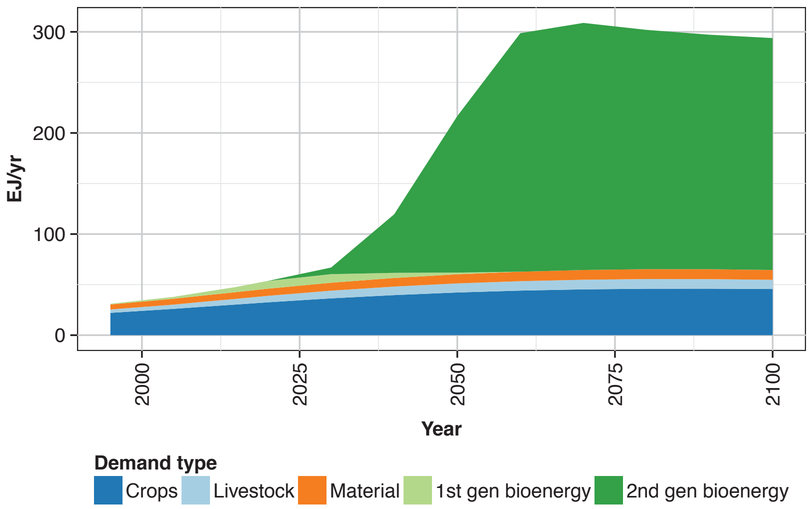

Figure S2: Time-series of global food (crops and livestock), material, 1st generation and 2nd generation bioenergy demand between 1995 and 2100 in EJ/yr. Food and material demand is calculated using the methodology described in Bodirsky *et al*[5] and the SSP2 population and GDP projections[6]. 1st generation and 2nd generation bioenergy demand is taken from the 450 FullTech ReMIND/MAgPIE scenario in Popp *et al*[7].

1.4. Carbon prices

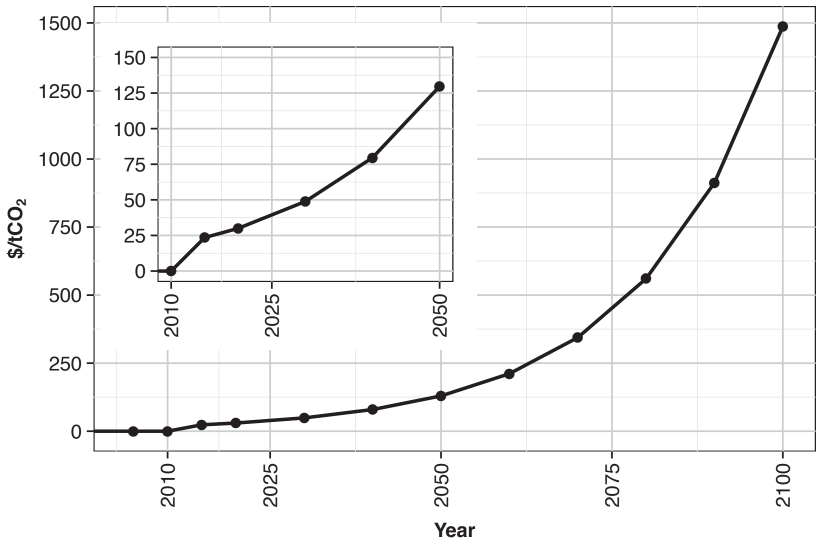

Figure S3: Time-series of the globally uniform price on land-related CO_2 emissions between 1995 and 2100 in $/$tCO_2$. The carbon price starts at 24 $/$tCO_2$ in 2015 and increases non-linearly at a rate of 5% per year, reaching 130 $/$tCO_2$ in 2050, and 1487 $/$tCO_2$ in 2100[8].

1.5. Land types

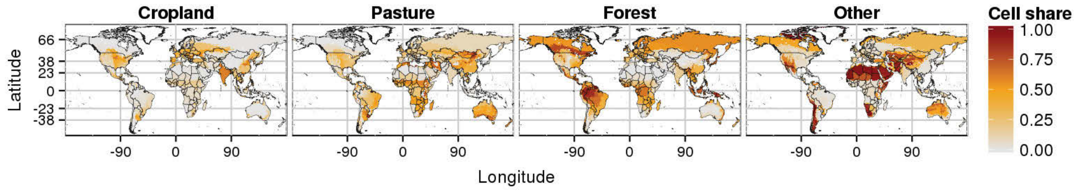

Figure S4: Initial (year 1995) spatially explicit land-use patterns for four land types used as input in the MAgPIE model[9]. Colours indicate the share of the respective land type in each cell. The sum of shares across the four land types for a single cell equals one.

1.6. Carbon densites

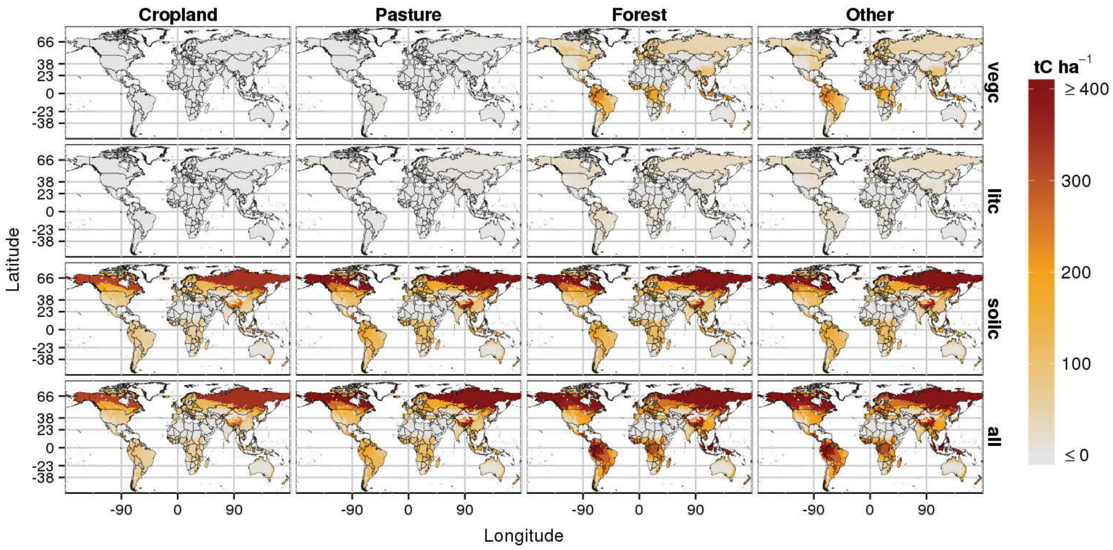

Figure S5: Spatially explicit carbon density (tC ha^{-1}) for four land types and the three carbon pools vegetation, litter and soil (vegc, litc, soilc) used as input in the MAgPIE model for the initial time step (year 1995). The last row (all) shows the cell-specific sum of vegetation, litter and soil carbon densities for each land type. The carbon densities are derived using the global biophysical process model LPJmL[10,11]. Cropland and pasture carbon densities are estimated based on LPJmL and data from IPCC[12] (chap 5–6, table 5.5 and 6.2). For forest and other land, the LPJmL information is used without modification for all carbon pools. The carbon densities shown here reflect potential carbon densities that just inform the MAgPIE model about the carbon density of cells that are completely covered by a specific land type. The actual cell-specific carbon density in MAgPIE depends on the land allocation within each cell (see Figure S4). For instance, a cell consisting of 50% cropland and 50% forest will end up with the average carbon pools specific carbon density of cropland and forest.

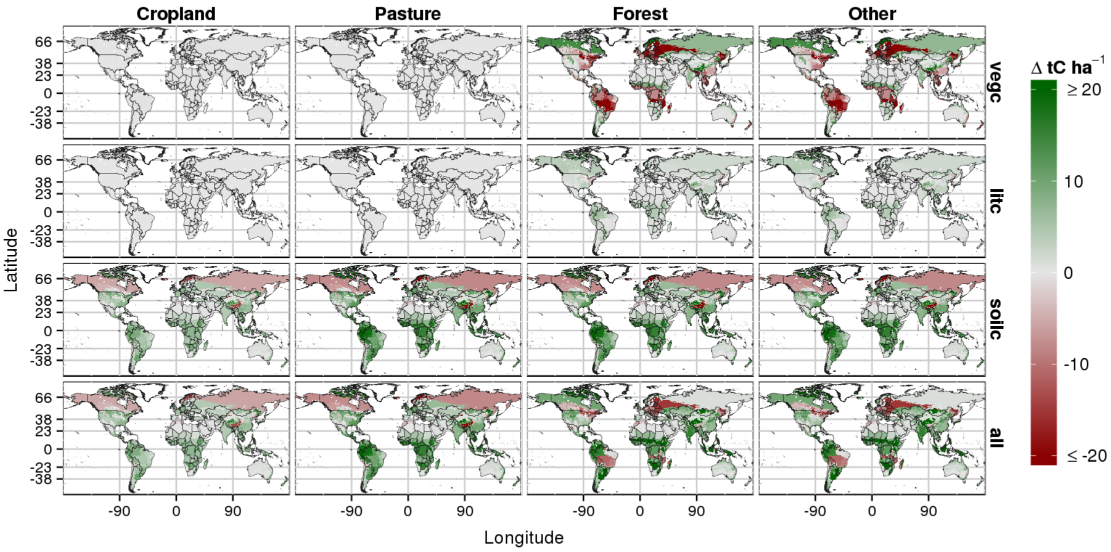

Figure S6: Spatially explicit change in carbon density (tC ha^{-1}) between 1995 and 2100 for RCP2.6 climate projections derived by the global biophysical process model LPJmL[10,11] (see Figure S5 for initial carbon densities and carbon pool abbreviations). LPJmL considers the reaction of the terrestrial biosphere to altered climatic conditions, such as temperature-enhanced respiration (loss of carbon) and increased photosynthetic activity due to elevated atmospheric CO_2 concentrations (gain of carbon). LPJmL derives such climate-induced changes in carbon densities for each simulation time step of MAgPIE. Changes in carbon densities reflect potential changes, i.e. the actual change in carbon density of a cell in MAgPIE depends on the cell-specific land allocation (see caption of Figure S5 for details). This plot shows average values over the five GCM-specific RCP2.6 climate projections used in this study.

1.7. Crop yields

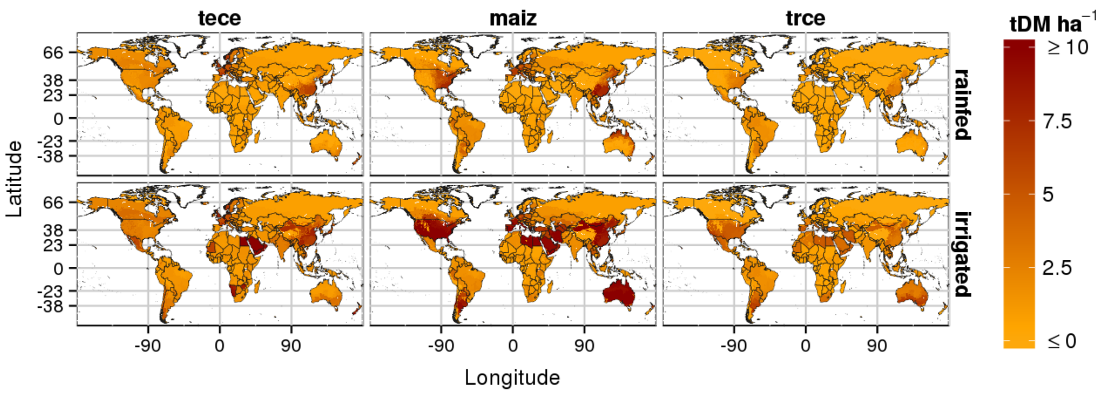

Figure S7: Spatially explicit rainfed and irrigated crop yields (tDM ha^{-1}) for the three crop types temperate cereals (tece), maize (maiz) and tropical cereals (trce) derived from the global biophysical process model LPJmL for the year 1995[10,11]. MAgPIE uses crop yields from LPJmL as input. In total, MAgPIE considers 17 crop types, each rainfed and irrigated: tece, maiz, trce, soybean, rapeseed, groundnut, sunflower, oil palm, pulses, potato, cassava, sugar cane, sugar beet, cotton, woody bioenergy and herbaceous bioenergy. The crop yields supplied by LPJmL are potential in two ways. First, as for carbon densities (see Figure S5), the LPJmL crop yields inform the MAgPIE model about the yield of cells that are completely covered with single crops. The actual cell-specific yield emerges from the mix of crops that is actually used within a cell. Second, the LPJmL crop yields represent yields achieved under the best currently available management options. Since MAgPIE aims to represent observed yields for the initial time step, LPJmL yields are calibrated, on the 10-region level, to observed yields taken from the FAO[13].

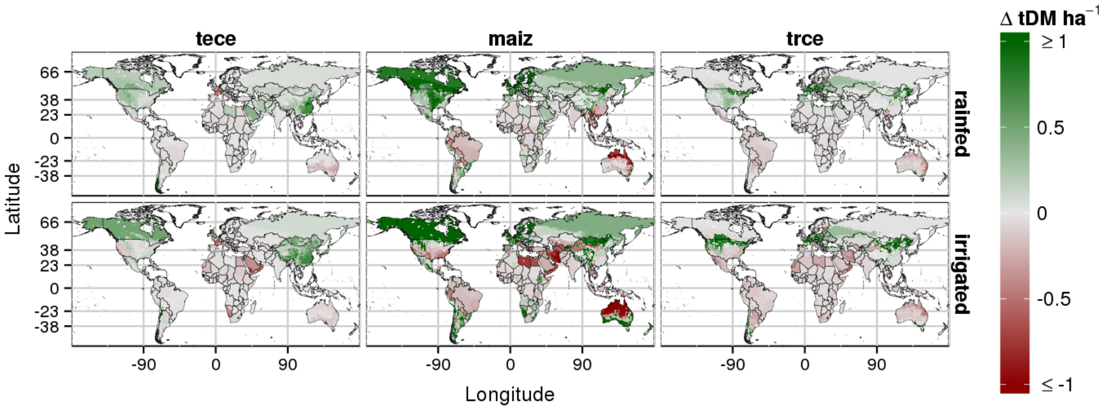

Figure S8: Spatially explicit change in crop yields (tDM ha^{-1}) between 1995 and 2100 for RCP2.6 climate projections derived by the global biophysical process model LPJmL[10,11] (see Figure S7 for initial crop yields and abbreviations). LPJmL considers the impact of changes in temperature, precipitation and CO_2 concentration (including CO_2 fertilization) on crop yields. LPJmL derives such climate-induced changes in crop yields for all crop types (see Figure S7) and for each simulation time step of MAgPIE. Changes in crop yields reflect potential changes, i.e. the actual change in the crop yield of a cell in MAgPIE depends on the cell-specific crop type allocation (see caption of Figure S7 for details). This plot shows average values over the five GCM-specific RCP2.6 climate projections used in this study.

1.8. Harmonization of biophysical input data

The biophysical process model LPJmL[10,11] translates RCP2.6 climate projections from five different GCMs (HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, GFDL-ESM2M and NorESM1-M)[14] into changes in crop yields and carbon densities. The climate projections, as supplied by the GCMs, differ for the historic period so that simulated crop yields and carbon densities for the reference period differ between the GCMs-specific climate projections. To facilitate comparison of outcomes, the results of the five GCM-specific biophysical climate impact simulations of the RCP2.6 climate projections have been harmonized for the initial MAgPIE time step. Yield harmonization is achieved by defining a reference GCM (HadGEM2-ES) and multiplication of the relative changes (all time steps divided by initial time step) of all other GCMs with this reference. This method preserves the relative differences and assures that the input data is identical for the initial time step. For carbon densities, this approach leads to a distortion of the temporal dynamics compared to the original data. Therefore, GCM specific differences with respect to 1995 have been added to the 1995 reference value. Resulting negative values are set to 0 and values that exceed the maximum carbon density in the original data have been cut off.

2. Detailed results

2.1. Agricultural yields

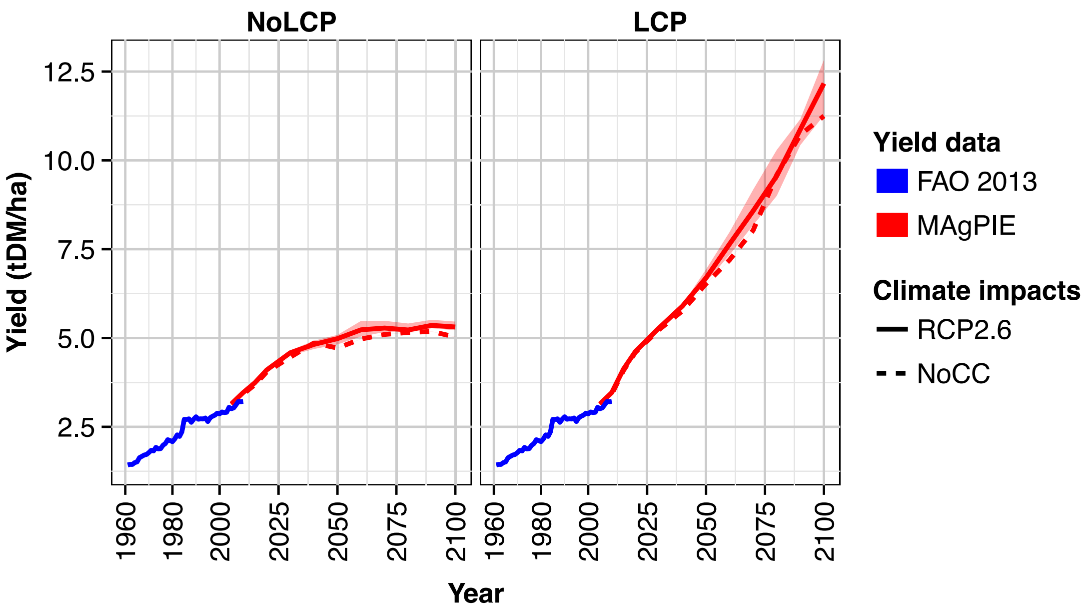

Figure S9: Time-series of global average food and feed crops yields (t DM ha^{-1}). The blue line shows historical data on agricultural yields taken from the FAO[13]. The red color depicts simulated agricultural yields from MAgPIE. For the MAgPIE data, the combinations of climate policy (*NoLCP*, *LCP*; left vs. right column) and climate impacts (*RCP2.6*, *NoCC*; solid vs. dashed lines) result in four scenarios. Solid lines represent the average over individual model results for five GCM-specific RCP2.6 climate projections, while shaded areas indicate the full range of results.

2.2. Land-use dynamics

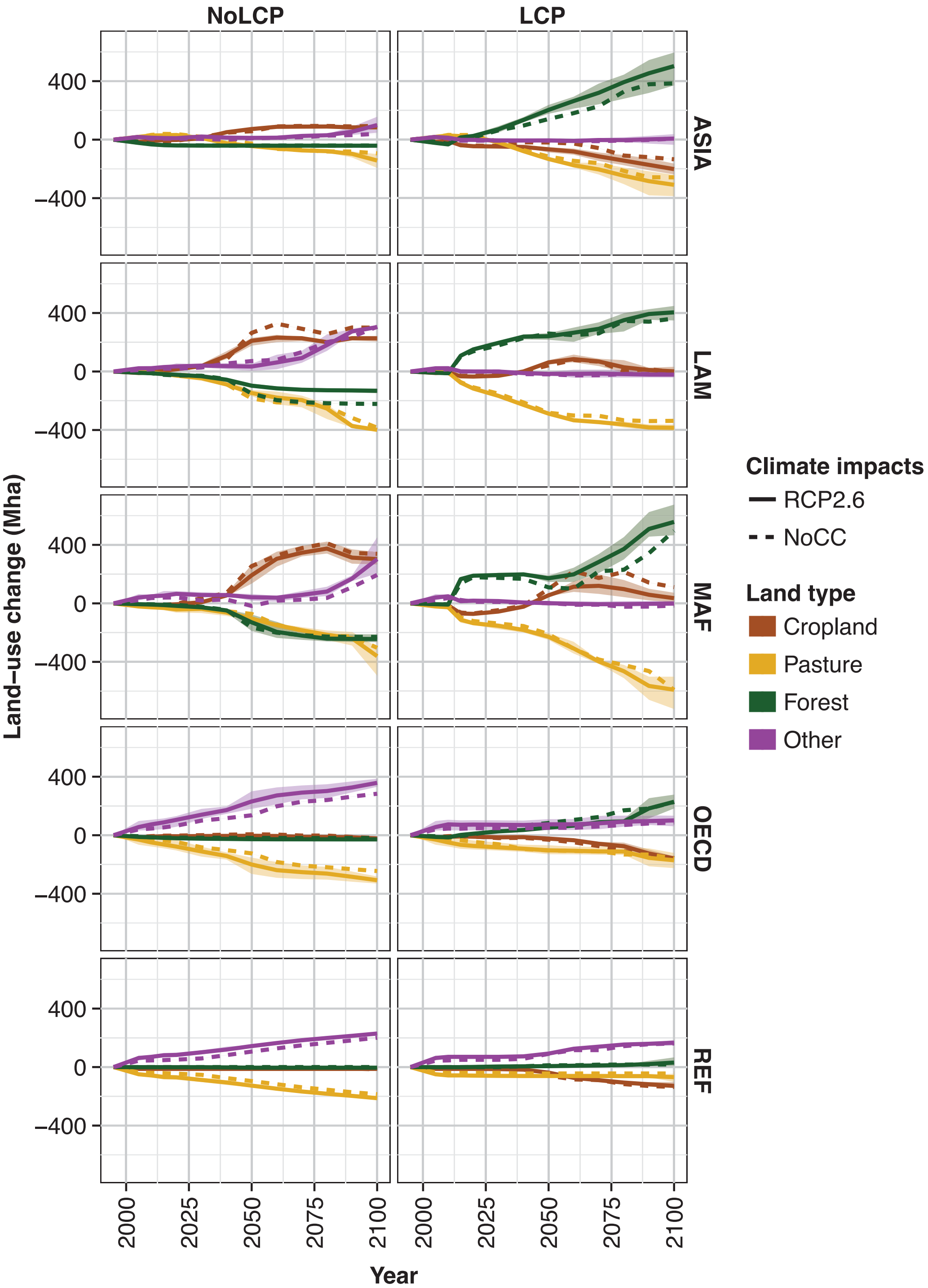

Figure S10: Time-series of regional land-use change (Mha) for four major land types between 1995 and 2100. The combinations of climate policy (*NoLCP*, *LCP*; left vs. right column) and climate impacts (*RCP2.6*, *NoCC*; solid vs. dashed lines) result in four scenarios. Solid lines represent the average over individual model results for five GCM-specific RCP2.6 climate projections, while shaded areas indicate the full range of results.

2.3. Carbon stock dynamics

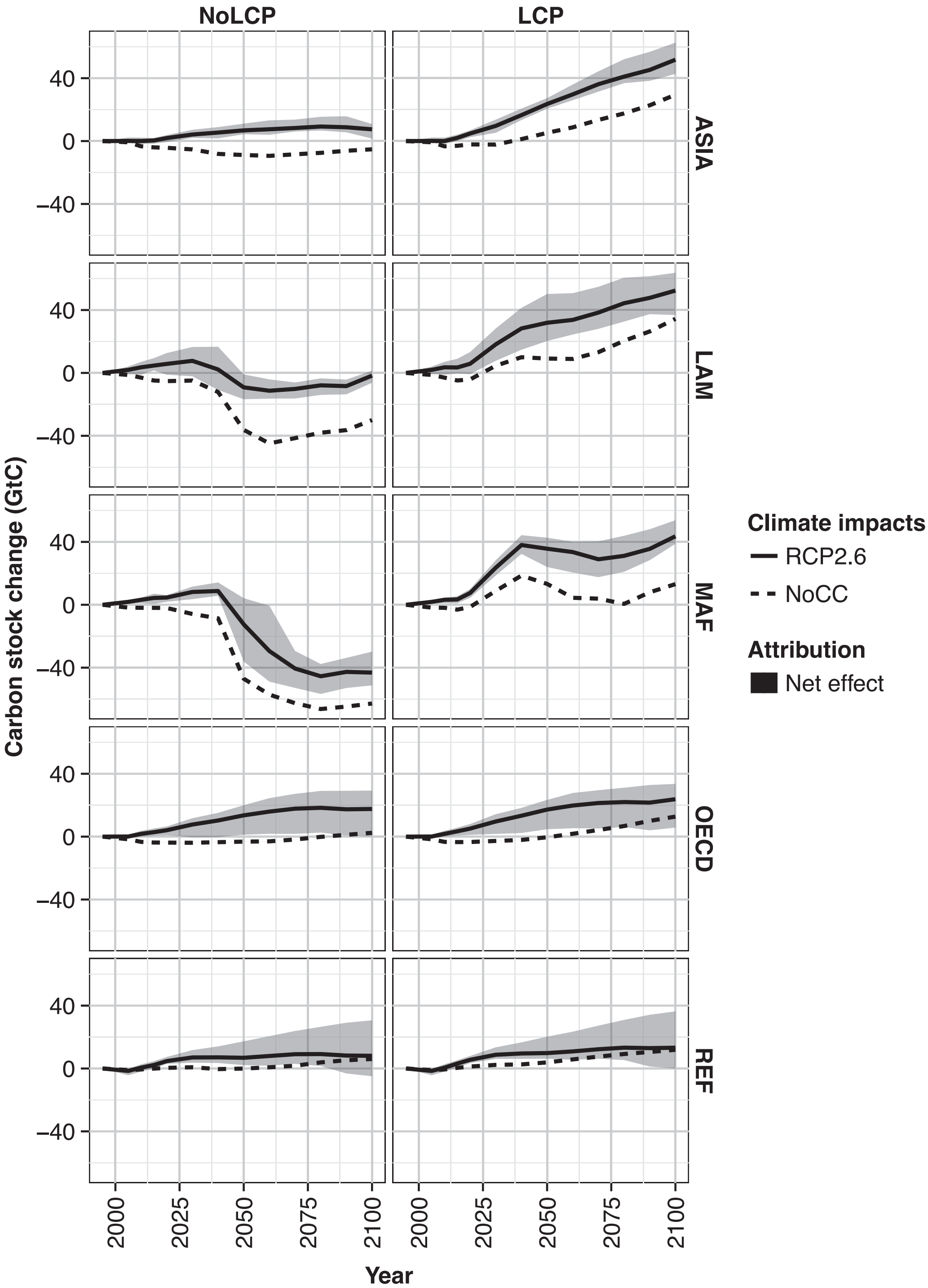

Figure S11: Time-series of regional terrestrial carbon stock change (GtC) between 1995 and 2100. The combinations of climate policy (*NoLCP*, *LCP*; left vs. right column) and climate impacts (*RCP2.6*, *NoCC*; solid vs. dashed lines) result in four scenarios. Solid lines represent the average over individual model results for five GCM-specific RCP2.6 climate projections, while shaded areas indicate the full range of results.

2.4. Validation

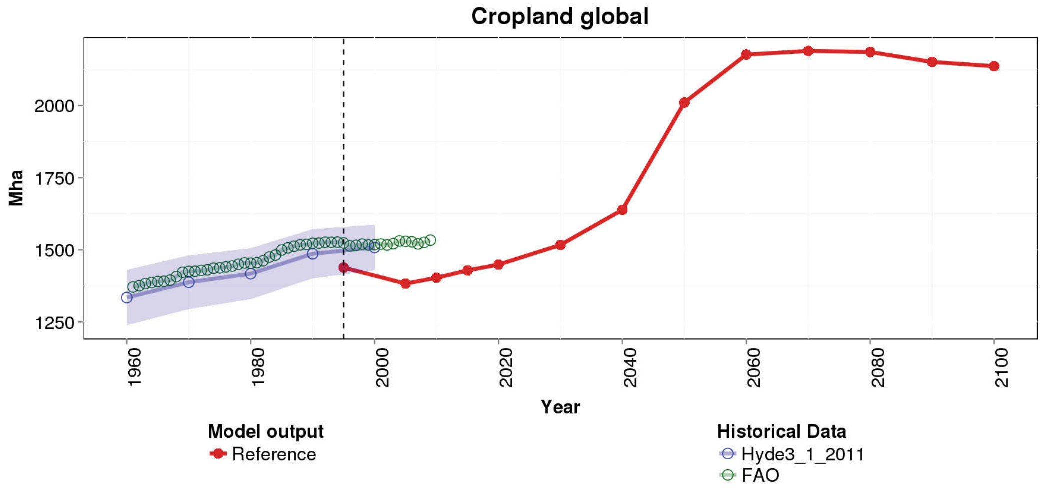

Figure S12: Time-series of simulated global cropland for the reference scenario, and historical data from the HYDE 3.1 dataset[15] and FAO[13]

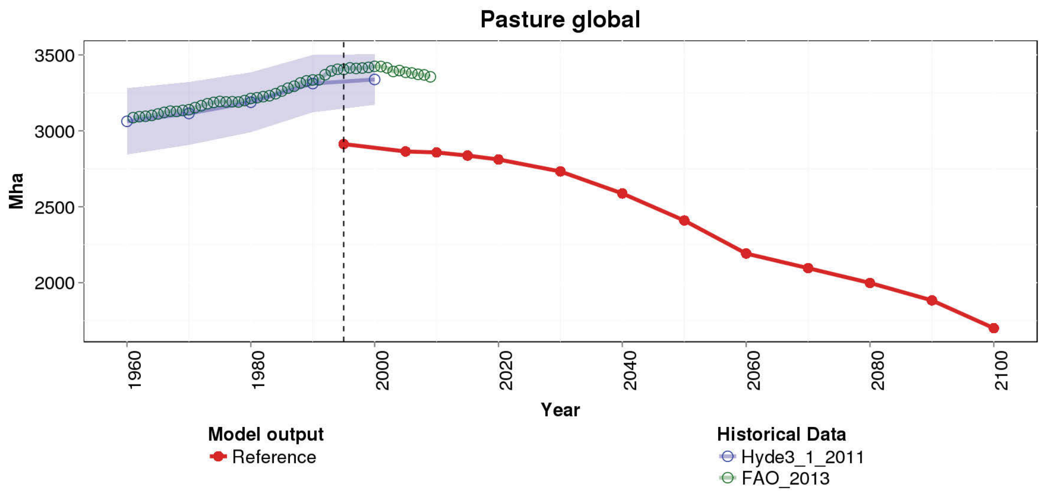

Figure S13: Time-series of simulated global pasture land for the reference scenario, and historical data from the HYDE 3.1 dataset[15] and FAO[13]

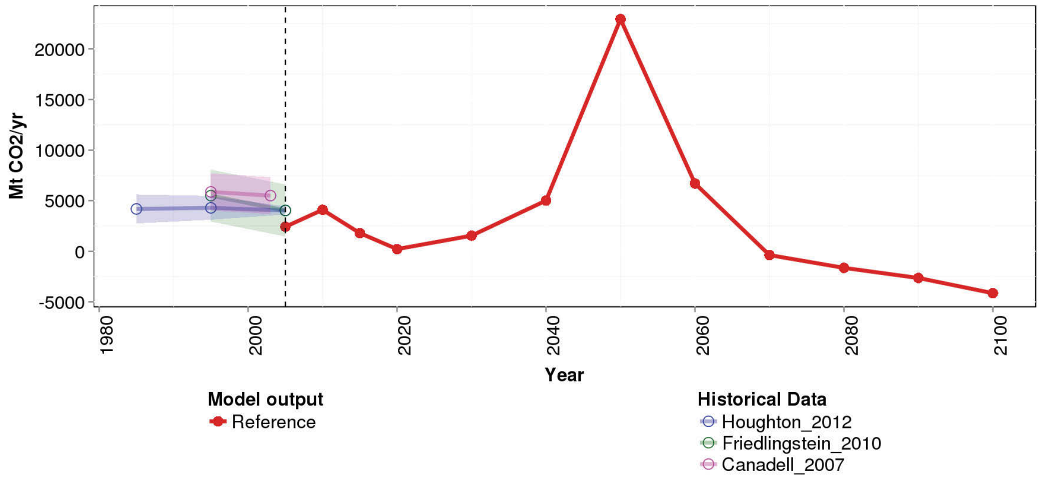

Figure S14: Time-series of simulated global land-use change emissions for the reference scenario, and historical data from Houghton *et al*[16], Friedlingstein *et al*[17] and Canadell *et al*[18].

2.5. *GCM-specific results*

		NoLCP				LCP			
		Cropland	**Pasture**	**Forest**	**Other**	**Cropland**	**Pasture**	**Forest**	**Other**
RCP2.6	HadGEM2_ES	601	-1442	-475	1316	-486	-1638	1914	210
	IPSL_CM5A_LR	547	-1412	-430	1295	-413	-1387	1461	339
	MIROC_ESM_CHEM	572	-1516	-445	1389	-431	-1762	1944	249
	GFDL_ESM2M	599	-1329	-442	1172	-505	-1483	1708	280
	NorESM1_M	576	-1416	-455	1295	-426	-1351	1593	184
	Mean	579	-1423	-449	1293	-452	-1524	1724	253
NoCC	Static climate	698	-1212	-511	1025	-319	-1390	1489	220

Table S2: GCM-specific land-use change (Mha) for four land types between 1995 and 2100. The combinations of climate policy (*NoLCP*, *LCP*; horizontal axis) and climate impacts (*RCP2.6*, *NoCC*; vertical axis) result in four scenarios.

		NoLCP			LCP		
		Net effect	**Land management**	**Direct climate change**	**Net effect**	**Land management**	**Direct climate change**
RCP2.6	HadGEM2_ES	-38	-73	34	161	125	37
	IPSL_CM5A_LR	-20	-67	47	161	114	47
	MIROC_ESM_CHEM	-30	-77	46	170	120	50
	GFDL_ESM2M	18	-74	92	224	129	95
	NorESM1_M	12	-77	89	207	110	97
	Mean	-12	-73	62	185	119	65
NoCC	Static climate	-90	-90	0	101	101	0

Table S3: GCM-specific carbon stock change (GtC) between 1995 and 2100 at the global scale. The combinations of climate policy (*NoLCP*, *LCP*; horizontal axis) and climate impacts (*RCP2.6*, *NoCC*; vertical axis) result in four scenarios. *Land management* reflects carbon stock changes associated with the land-use dynamics shown in Table S2 and includes indirect effects of climate change on carbon stocks through land-use responses. *Direct climate change* reflects carbon stock changes due to direct impacts of climate change on carbon sequestration in the terrestrial biosphere. The *net effect* on carbon stocks is represented by the sum of *land management* and *direct climate change*.

3. References

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VII Synthesis and Outlook

1 Summary of results

This thesis investigates the potential contribution of the global land system to climate change mitigation in the 21st century by using the spatially explicit economic land-use optimization model MAgPIE. This section summarizes the results of chapters II-VI along the research questions formulated in chapter I.

Chapter II What is the carbon mitigation potential of global forest and land-use protection schemes?

Chapter II analyzed the contribution of global land-use protection schemes to climate change mitigation throughout the 21st century with the MAgPIE model. Global land-use protection was implemented by pricing CO_2 emissions from deforestation (forest protection) and all land-use changes (comprehensive land-use protection).

Under a global forest protection scheme, agriculture no longer expands into forests as it happens in the reference scenario because pricing CO_2 emissions from deforestation renders forest-to-cropland conversion economically unattractive (182 Mha less deforestation until 2100). Instead, agriculture expands into areas that are not under emission control but still contain considerable amounts of carbon. Therefore, land-use change emissions still accumulate to 96 $GtCO_2$ until 2100. However, the forest protection scheme reduces global cumulative land-use change emissions by 77 $GtCO_2$ until 2100 compared to the reference scenario. Moreover, the global forest protection scheme reduces the abandonment of agricultural land to compensate for missing access to forest. Therefore, global carbon uptake from regrowth of natural vegetation on abandoned agricultural land drops by 29 $GtCO_2$ until 2100 under forest protection. The cumulative net mitigation potential (including land-use change emissions and carbon uptake due to ecological succession) that can be attributed to land management under the global forest protection scheme is 48 $GtCO_2$ (77 $GtCO_2$ - 29 $GtCO_2$) throughout the 21st century.

Pricing CO_2 emissions from all land-use changes under the comprehensive land-use protection scheme results in a quite static land-use system since, besides deforestation, also most other land conversions come to hold. Cropland expands only by 35 Mha until 2100 compared to 203 Mha in the forest protection scenario. In consequence, global cumulative land-use change emissions are 78 $GtCO_2$ lower in 2100 compared to the forest protection scenario. However, these emission reductions come at the cost of higher agricultural yield increases that are required to maintain food production with less agricultural area. The comprehensive land-use protection scheme reduces carbon uptake due to regrowth of natural vegetation by another 27 $GtCO_2$ until 2100 because even less agricultural land is abandoned than in the forest protection scenario. The global cumulative net mitigation potential of the comprehensive land-use protection scheme is 51 $GtCO_2$ (78 $GtCO_2$ - 27 $GtCO_2$) higher than that of the forest protection scheme in 2100. Therefore, extending a global forest protection scheme to all land-use changes could double the associated mitigation potential, but would require larger yield increases in the agricultural sector.

Sensitivity analysis showed that the mitigation potential of global land-use protection schemes strongly depends on demand and supply side assumptions. For instance, a demitarian food demand scenario that limits the share of livestock products to 15% of total caloric consumption, which is equivalent to about half of the current livestock consumption in OECD countries, lowers the pressure on the land system, leading to less agricultural expansion – at least under the global forest protection scheme. Demitarian food demand does not further reduce agricultural expansion under the comprehensive land-use protection scheme since carbon prices render agricultural expansion unattractive already in the default setting with higher food demand (see above). Thus, demitarian food demand lowers emissions from land-use change by 23% under the global forest protection scheme but does not affect land-use change emissions under comprehensive land-use protection. Contrary, assuming higher costs for yield-increasing technological change increase agricultural expansion under the forest and the comprehensive protection scheme, leading to 49% and 45% higher land-use change emissions, respectively. Carbon stock changes due to impacts of climate change (RCP2.6) on crop yields and carbon sequestration in the terrestrial biosphere hardly differ across the scenarios.

Chapter III How much bioenergy can be supplied at what price, with and w/o GHG emissions pricing in the land system?

Chapter III presented global bioenergy supply curves with and w/o GHG emissions pricing in the land system. The supply curves were constructed by deriving bioenergy supply prices, which are represented by the marginal costs of bioenergy production, for 73 bioenergy demand scenarios with the MAgPIE model. In the model simulations, bioenergy demand was prescribed only at the global scale. Thus, the regional allocation of bioenergy production happened endogenously in the model based on cost-effectiveness.

Bioenergy can be supplied starting from prices of 5$/GJ. Without GHG emissions pricing, global bioenergy supply prices increase almost linearly with global bioenergy demand, reaching 10 $/GJ at 145 EJ/yr in 2055 and 13 $/GJ at 240 EJ/yr in 2095. Introducing a price on GHG emissions increases global bioenergy supply prices by 5 $/GJ in 2055 (50%) and 10 $/GJ in 2095 (77%). Thus, bioenergy supply prices increase non-linear with bioenergy demand under GHG emissions pricing. This elevating impact of GHG emissions prices on the bioenergy supply curve can be separated into a steepening and a shifting effect. The carbon price on emissions from deforestation causes the steepening effect. Carbon pricing effectively stops deforestation and thereby reduces the availability of high-productive land, mainly in tropical regions, for cropland expansion. Displacing cropland expansion to non-forest areas that are not under emission control partly alleviates this land scarcity. Nevertheless, the land scarcity induced by the carbon price becomes pressing with increasing bioenergy demand levels, which is reflected in bioenergy supply prices that scale with bioenergy demand. Pricing N_2O emissions from fertilizer application causes the shifting effect. The shifting effect does not scale with bioenergy demand because the required amount of organic and inorganic fertilizer input per unit of bioenergy output is assumed constant.

The production of 240 EJ bioenergy in 2095 requires almost 500 Mha of cropland globally, regardless of the GHG emissions pricing regime. Without GHG emissions pricing, forests can be converted at relativity low costs to productive cropland, in particular in tropical regions. Thus, Africa and Latin America are the major bioenergy producers in this case, accounting for about two-thirds of global bioenergy production. Due to missing access to forests, the share of global bioenergy produced in Africa and Latin America drops to about one-third under GHG emissions pricing, while regions with productive non-forest land that is not under emission control gain. In consequence, cumulative CO_2 emissions until 2095 associated with land-use change drop from 297 to 200 $GtCO_2$ with the introduction of GHG emissions pricing. These numbers include only CO_2 emissions from land-use change due to food and bioenergy production. In particular, emissions or emission savings due to bioenergy use in combination with CCS are not included here.

Chapter IV How does irrigation in bioenergy production affect land and water resources, and what are the impacts on bioenergy prices?

Chapter IV explored the trade-offs between land and water requirements for large-scale bioenergy production compatible with a 450 ppm CO_2eq stabilization target in 2100. For this purpose two scenarios were analyzed with the MAgPIE model: fulfillment of an exogenous global bioenergy demand path (300 EJ in 2095) with and w/o irrigation of bioenergy crops.

As in chapter III, regional allocation of bioenergy production happens endogenously in the model. If irrigation of bioenergy crops is allowed, Latin America is the dominant production region in 2095 (160 EJ), followed by South Asia (40 EJ), North America (35 EJ), Sub-Saharan Africa (30 EJ), and China (30 EJ). The share of irrigated bioenergy production is 95% in South Asia, 73% in Sub-Saharan Africa, 71% in North America, 50% in Latin America and 10% in China. In total, 58% of global bioenergy supply in 2095 originates from irrigated production. If a water protection policy prohibits irrigated bioenergy production, all bioenergy feedstock is provided from rainfed agriculture. End-of-21st century bioenergy production remains largely stable in Latin America (160 EJ), China (35 EJ), and North America (30 EJ), but South Asia is no longer competitive (0 EJ). To compensate for this, bioenergy production increases in other regions, mainly in Sub-Saharan Africa (65 EJ in 2095).

Global agricultural water withdrawals in 2095 amount to 6400 km^3, up from 2926 km^3 in 1995, if irrigation of bioenergy crops is not regulated. In contrast, if irrigation of bioenergy crops is prohibited, agricultural water withdrawals in 2095 (3000 km^3) are close to the initial value in 1995. Under irrigation of bioenergy crops, regions with high agricultural water withdrawals coincide with regions showing high shares of irrigated bioenergy production (South Asia, Sub-Saharan Africa, North America, and Latin America)

In the unrestricted irrigation scenario, producing 300 EJ bioenergy requires 490 Mha dedicated bioenergy cropland in 2095, whereof 228 Mha are irrigated. If bioenergy is produced only rainfed, 200 Mha additional bioenergy cropland is required in 2095 (41% more) owing to lower yields compared to irrigated production. Cropland requirements for bioenergy as well as for food and feed crop production are fulfilled at the expense of pasture and natural forests.

Bioenergy supply prices increase to 7.6 $/GJ in 2095, up from 5$/GJ in 2015, if bioenergy crop irrigation is allowed. Under prohibition of bioenergy crop irrigation, bioenergy supply prices for producing 300 EJ bioenergy in 2095 are around 20% higher (9.2 $/GJ) because the costs for additional land conversion increase the marginal costs of production.

In the default setting, water productivity (output produced per unit of water) scales with yield increases, whereupon bioenergy crops benefit in the same way from yield-increasing technological change as traditional crops. If water productivity is static (fixed water requirements per unit output), water withdrawals increase by 38% in the unrestricted irrigation scenario in 2095. At the same time, the share of irrigated bioenergy area drops from 47% to 25%. To compensate for the reduction of irrigated bioenergy area, total bioenergy area increases by 16%, associated with 24% more deforestation. If bioenergy crops benefit only half as much from yield-increasing technological change as traditional crops, 52% more bioenergy area is needed for producing 300 EJ bioenergy in 2095, associated 33% more deforestation and 30% higher water withdrawals.

Chapter V How much land do afforestation and bioenergy with CCS require for how much CDR?

Chapter V investigated the global CDR potential of large-scale afforestation, bioenergy use with CCS, and the combination of both for the 21st century with the MAgPIE model. In the model simulations, the level of deployment of these two options was derived endogenously based on cost-effectiveness. A price on GHG emissions, extended to rewarding negative CO_2 emissions, provided incentives for afforestation and/or bioenergy with CCS.

Afforestation emerges as cost-efficient CDR strategy with the introduction of the carbon price in 2015 at a level of 24$/t$CO_2$. By the end of the 21st century, the global land area in use for afforestation amounts to 2773 Mha, which reflects an increase of the current global forest area by about two-thirds. Land for afforestation mainly originates from the conversion of agricultural land (croplands and pastures). Bioenergy with CCS requires much higher incentives than afforestation for deployment. From 2065, at carbon prices of 270 $/t$CO_2$, bioenergy area starts to increase, mainly at the expense of cropland, and reaches 508 Mha in 2095. Bioenergy production amounts to 237 EJ in 2095. In the combined setting, global afforestation and bioenergy area in 2095 are both smaller than in the respective standalone setting (afforestation 2566 Mha, bioenergy 300 Mha), which reflects that afforestation and bioenergy with CCS compete for productive land. Such a large-scale transformation of the global land surface in favor of afforestation and bioenergy deployment requires substantial yield increases in the agricultural sector. On average, global agricultural yields would need to increase by 1.37% per year until 2095 to keep food consumption levels unaffected from land-based mitigation. These average annual yield increases imply more than a tripling of current agricultural yields throughout the 21st century.

In the standalone settings, the global CDR of large-scale afforestation accumulates to 703 GtCO_2 until 2095, while bioenergy with CCS reaches a global cumulative CDR of 591 GtCO_2 in 2095. Thus, afforestation requires about five times as much land as bioenergy with CCS for a similar CDR in 2095. On the other hand, bioenergy crop production causes additional N_2O emissions from increased fertilizer use, although N_2O emissions are priced. These additional N_2O emissions reduce the net effect of CDR attributable to bioenergy with CCS by about 50 GtCO_{2eq} throughout the 21st century. The global CDR in the combined setting amounts to 1000 GtCO_2 in 2095. While CDR from afforestation drops from 591 to 409 GtCO_2, CDR from bioenergy with CCS remains at 591 GtCO_2. Thus, large-scale early-century afforestation does not negatively affect CDR from bioenergy with CCS in the second half of the 21st century.

Sensitivity analysis showed that the level of land-based CDR strongly depends on the level of carbon prices. For instance, a carbon price trajectory with prices of 5 $/t$CO_2$ in 2020, instead of 30$/t$CO_2$ as in the default setting, reduces afforestation by about 30% and associated CDR by about 43% in 2095. At such low carbon prices, bioenergy with CCS is no longer a cost-efficient CDR option. Moreover, for afforestation projects, the length of the fixed crediting period is a crucial factor. If the fixed crediting period is 10 years, instead of 30 years as in the default setting, afforestation is about 46% lower in 2095, associated with about 40% less CDR. Furthermore, deployment of bioenergy with CCS depends on the future development of bioenergy yields and the availability of geological storage capacity. If bioenergy yields remain at current levels, instead of increasing over time due to technological progress in the agricultural sector as in the default setting, CDR due to bioenergy with CCS in 2100 is about 80% lower, while land requirements are similar to the default setting. If the global geological carbon injection rate is limited to 1 $GtCO_2$/yr, instead of 20 $GtCO_2$/yr as in the default setting, bioenergy deployment for use with CCS is close to zero.

Chapter VI What are the direct and indirect effects of moderate climate change on terrestrial carbon stocks and what are the implications for land-based carbon mitigation?

Chapter VI addressed global scale interactions between the climate system, anthropogenic land-use and the terrestrial carbon balance in the context of moderate climate change and a land-based climate policy that fosters large-scale afforestation and avoidance of deforestation. In the model simulations, afforestation was prohibited in high-latitude regions due potential counteracting albedo effects. For comparability with other findings of this thesis, carbon stock changes are report here in $GtCO_2$, while in chapter VI carbon stock changes are reported in GtC.

Under a land-based climate policy that prices CO_2 emissions from all land-use changes and rewards CDR from afforestation, deforestation is immediately replaced by large-scale afforestation. From 2015, when the carbon price in introduced at 24\$/tCO_2, global forest area increases by 1489 Mha until 2100, which reflects an increase of the current global forest area by about one-third throughout the 21st century. Land for afforestation originates from the conversion of agricultural land. Maintaining food supply under such large-scale reductions of agricultural land requires average yield increases of 1.36% per year until 2100, which implies more than a tripling of current agricultural yields in the course of the 21st century. Under the land-based climate policy, global carbon stocks increase by 370 $GtCO_2$ until 2100. In the reference scenario without climate policy, carbon stocks decrease globally by 330 $GtCO_2$ until 2100, mainly due to deforestation. Therefore, the global mitigation potential attributed to the land-based climate policy is 700 $GtCO_2$ in 2100. These numbers include CO_2 emissions from the production of modern bioenergy consistent with GHG stabilization at 450 ppm CO_2eq in 2100 / RCP2.6, but exclude potential emissions or emission savings from bioenergy use in combination with CCS.

Due to beneficial effects on global agricultural yields, RCP2.6 climate impacts reduce global agricultural land requirements by 330 Mha throughout the 21st century compared to the reference scenario without further climate change (static climatic conditions at 1995 levels). In consequence, less deforestation for agricultural expansion takes place owing to RCP2.6 climate impacts. Thus, direct impacts of climate change on agricultural yields indirectly affect carbon stocks through altered land management. In addition, RCP2.6 climate impacts increase the abandonment of agricultural land, associated with regrowth of natural vegetation. In total, land-use responses to RCP2.6 climate impacts result in 59 $GtCO_2$ higher terrestrial carbon stocks in 2100 compared to the reference scenario. In addition, climate change has direct effects on carbon stocks, in particular in forests. Due to enhanced carbon sequestration, global terrestrial carbon stocks are 227 $GtCO_2$ higher in 2100 compared to the reference scenario. From the total global climate-change-induced carbon stock gains (286 $GtCO_2$), 21% (59 $GtCO_2$) are caused indirectly through altered land management. Uncertainties in results introduced by different climate projections for RCP2.6 do not qualitatively alter this finding, which underpins the relevance of land-use dynamics for simulating carbon cycle responses to climate change. The current generation of IAMs does not account for such land-use responses to climate change in their carbon balance. Thus, better representation of the interactions between the climate system, anthropogenic land-use and the terrestrial carbon balance in IAMs could play a vital role for improving projections of future mitigation efforts and costs.

In the combined setting, such beneficial climate impacts on terrestrial carbon stocks only marginally increase the potential that can be attributed to land-based carbon mitigation throughout the 21st century. The main reason for this low interaction between RCP2.6 climate impacts and land-based carbon mitigation is that the mitigation potential of afforestation and avoidance of deforestation is already large without further climate change.

2 Key findings

This section presents the key findings across chapters II-VI that contribute to answering the overarching research questions formulated in chapter I of this thesis: *What is the global potential of land-based carbon mitigation in the 21st century, what are the associated land requirements and what are the implications for the agricultural sector?*

Avoidance of land-use change emissions

- Including CO_2 emissions from deforestation in a global carbon pricing mechanism immediately stops deforestation. Such forest protection lowers emissions from land-use change by 77 $GtCO_2$ cumulatively throughout the 21st century. However, due to displacement of agricultural expansion to non-forest land types, global emissions from land-use change still accumulate to 96 $GtCO_2$ until 2100. Lower food demand attenuates the pressure on the land system, leading to a reduction of emissions from land-use change by 23%. Contrary, higher costs for yield-increasing technological change cause more agricultural expansion, resulting in 49% higher emissions from land-use change. *Chapter II*

- Pricing all land-use change emissions globally results in a quite static land-use system. Accordingly, global land-use change emissions accumulate to only 18 $GtCO_2$ until 2100. However, maintaining food production with less agricultural expansion requires larger yield increases in the agricultural sector. In this setting, emissions from land-use change are insensitive to lower food demand but increase by 45% under higher costs for agricultural intensification. *Chapter II*

- Pricing emissions from deforestation effectively excludes forests from the available land for agricultural expansion. To compensate for this *Chapter II* land scarcity, less agricultural land is abandoned under carbon pricing. Thus, carbon uptake from regrowth of natural vegetation on abandoned agricultural land that happens without carbon pricing is hampered.

Land requirements and mitigation potential of bioenergy with CCS and afforestation

- In a standalone setting, the global CDR from large-scale afforestation amounts to 703 $GtCO_2$ in 2095, associated with land requirements of 2773 Mha, while the global CDR from bioenergy with CCS amounts to 591 $GtCO_2$, associated with land requirements of 508 Mha. The CDR per unit area is 4-5 times higher for bioenergy with CCS since one unit of land can be used several times for bioenergy production but just once for afforestation. However, bioenergy with CCS needs substantially higher carbon prices for cost-effective deployment (270 $/$tCO_2$) than afforestation (24 $/$tCO_2$). Maintaining food supply under such large-scale land-based mitigation requires considerable productivity increases in the agricultural sector (more than a tripling of current agricultural yields throughout the 21st century). *Chapter V*

- In a combined setting, global afforestation and bioenergy area are both smaller: 2566 Mha and 300 Mha in 2095, respectively. While the global CDR from large-scale afforestation drops to 409 $GtCO_2$, the CDR from bioenergy with CCS remains at 591 $GtCO_2$ in 2095. Thus, early-century afforestation at relatively low carbon prices does not interfere with the potential of bioenergy with CCS at higher carbon prices in the 2nd half of the 21st century. *Chapter V*

- The potential of land-based carbon mitigation strongly depends on the level of carbon prices. If carbon prices in 2020 amount to 5 $/$tCO_2$ instead of 30 $/$tCO_2$, bioenergy with CCS is no longer a cost-efficient CDR option. Moreover, CDR due to bioenergy with CCS is about 80% lower in 2100 if bioenergy yields remain at current levels instead of increasing over time. For afforestation projects, the length of the fixed crediting period is crucial. *Chapter V*

- Prohibition of afforestation in high-latitude regions reduces the global area in use for afforestation by 42% (1489 Mha vs. 2566 Mha in 2100). The CDR from afforestation, however, drops only by 10% (370 $GtCO_2$ vs. 409 $GtCO_2$ in 2100). This indicates that large-scale afforestation in high-latitude regions might not only be unfavorable from a biophysical (potential counteracting albedo effects) but also from a biogeochemical point of view (relatively low carbon sequestration rate per unit area). *Chapters V, VI*

- The IPCC's Working Group III attributes CDR from the use of bioenergy with CCS to the electricity sector, while the AFOLU sector includes GHG emissions from the production of biomass (Edenhofer et al., 2014a). *Chapter VI*

Following this accounting approach, the global mitigation potential of a land-based climate policy in the AFOLU sector that includes afforestation in low- and mid-latitude regions, avoidance of land-use change emissions, and bioenergy production compatible with RCP2.6 amounts to 700 $GtCO_2$ by the end of the 21st century.

Land-based climate policy and RCP2.6 climate impacts

- Due to beneficial effects on global agricultural yields and carbon sequestration in the terrestrial biosphere, RCP2.6 climate impacts increase global terrestrial carbons stocks by 286 $GtCO_2$ until 2100 compared to a reference case without further climate change. From the total climate-change-induced carbon stock gains, 21% are caused indirectly through altered land management since higher yields reduce cropland requirements, and hence deforestation. This finding underpins the relevance of land-use dynamics for simulating carbon cycle responses to climate change, which could be of particular importance for integrated assessment modeling. *Chapter VI*

- Beneficial RCP2.6 climate impacts on global terrestrial carbon stocks only marginally increase the potential that can be attributed to land-based carbon mitigation in the 21st century since the mitigation potential of afforestation and avoidance of deforestation is already large without further climate change. *Chapter VI*

Bioenergy production: land requirements, water withdrawals and supply prices

- Modern bioenergy can be supplied starting from prices of 5$/GJ. Without GHG emissions pricing, global bioenergy supply prices increase almost linearly with global bioenergy demand, reaching 10$/GJ at 145 EJ in 2055 and 13 $/GJ at 240 EJ in 2095. Introducing a price on GHG emissions in the land-use sector reduces the availability of forests for agricultural expansion, leading to an increase of bioenergy supply prices by 50% in 2055 and 77% in 2095. Thus, bioenergy supply prices increase non-linear with bioenergy demand under GHG emissions pricing. *Chapter III*

- Land scarcity due to pricing of emission from deforestation is partially alleviated by displacing agricultural expansion to land types that are not under emission control. Hence, GHG emissions pricing alters the regional allocation of bioenergy production. The share of global bioenergy production in regions with tropical forests, such as Africa and Latin America, drops from two-thirds to one-third, associated with a drop in cumulative CO_2 emissions from 297 to 200 $GtCO_2$ until 2095. *Chapter III*

- The production of 300 EJ bioenergy in 2095 requires about 500 Mha cropland globally if irrigation is unrestricted. To put this into perspective, 300 EJ is similar to the current global human appropriation of net primary production (Haberl et al., 2007) and 500 *Chapters III, IV, V, VI*

Mha represent about one-third of current global cropland (FAO, 2013a; Foley et al., 2011; Ramankutty et al., 2008). The same global area can provide 215-240 EJ bioenergy in 2095 if irrigation of bioenergy crops is prohibited and hence bioenergy production is rainfed only. The provision of 300 EJ bioenergy in 2095 under rainfed only production requires about 700 Mha cropland globally.

- Land requirements for bioenergy production strongly depend on the future development of bioenergy yields. For instance, bioenergy area is about 50% higher when bioenergy crops benefit only half as much from yield-increasing technological change as traditional crops. *Chapter IV*

- If irrigation of bioenergy crops is allowed, 58% of total bioenergy production in 2095 (300 EJ) is irrigated, associated with a doubling of current agricultural water withdrawals. In contrary, under rainfed only bioenergy production, agricultural water withdrawals in 2095 are close to current levels. *Chapter IV*

- Prohibition of irrigated bioenergy crop production can avoid additional pressure on global blue water resources but increases land requirement for bioenergy production by 41% (300 EJ in 2095). The additional pressure on land resources is reflected in an increase of bioenergy supply prices from 7.6 \$/GJ to 9.2 \$/GJ in 2095. Thus, the objective to provide 300 EJ bioenergy in 2095 and avoid additional pressure on blue water resources at the same time increases bioenergy supply prices by 20%. *Chapter IV*

- Improved representation of pasture dynamics attenuate the pressure in the land system, which is reflected in lower bioenergy supply prices: 13 \$/GJ associated with bioenergy demand of 240 EJ in 2095 if pasture area is assumed fixed (chapter III) vs. 9.2 \$/GJ associated with bioenergy demand of 300 EJ in 2095 if pasture area is dynamic (chapter IV). *Chapters III, IV*

3 Limitations

This thesis used methods of model-based computer simulation (MAgPIE model) and scenario analysis (food and bioenergy demand, carbon prices, climate impacts) to investigate the potential contribution of the global land system to climate change mitigation in the 21st century. This section highlights crucial assumptions and model limitations that need to be considered for the interpretation of the results of this thesis.

Socio-economic assumptions

Due to the inertia of the climate system, climate protection polices need a long-term horizon. Thus, the planning of climate polices requires projections of possible future pathways. This thesis provides future pathways for the land-use sector under ambitious climate policies. All scenario analyses in this thesis are based on the same socio-economic assumptions. However, the employed Shared Socio-economic Pathway (SSP2) is just one among many possible developments in the future (O'Neill et al., 2014). Other Shared Socio-economic Pathways show substantially different population and income dynamics along with different assumptions on land-use regulation and trade liberalisation that will affect the outcome of land-based climate polices in 21st century. Thus, for a more comprehensive picture, future research should explore land-based climate polices under different socio-economic assumptions.

Climate change governance

"In the real world, global cooperative action is unlikely to be implemented before 2020, and prospects thereafter are uncertain. In addition, models do not account for the institutional challenges that implementing a price on carbon may bring on the national to regional scale. All of these factors can substantially increase the mitigation challenge, including the costs of mitigation."
(Kriegler et al., 2014b, p. 366)

Another crucial assumption in this thesis is that the international community will agree in the near future on pricing CO_2 emissions and rewarding CDR in the land-use and energy sectors. Considering the progress in recent climate negotiations, such rather immediate climate action under full cooperation of all United Nations member states across economic sectors seems highly ambitious if not downright impossible. Future research could provide a more realistic picture by accounting for delayed and regionally/sectorally fragmented climate action in climate policy scenarios, as proposed by the concept of shared policy assumptions (SPAs) (Kriegler et al., 2014a). Moreover, pricing CO_2 emission and rewarding CDR implies the implementation of a monitoring, reporting and verification (MRV) system. The MAgPIE model, however, does not explicitly account for the build-up of institutions that operate such a MRV system.

Impacts of climate change

This thesis considered impacts of climate change on the land system based on RCP2.6 climate projections in chapter II and VI. This choice is consistent with the climate polices that have been assumed in these chapters. However, RCP2.6 is among the most ambitious climate protection scenarios that require almost immediate climate action at the global scale and across economic sectors (Edenhofer et al., 2014a). In case of delayed, regionally fragmented and/or sectorally fragmented climate action, RCP2.6 might be out of reach. Under higher RCPs, such as RCP4.5, RCP6.0 and RCP8.5, the impacts of climate change on the land system likely differ from those under RCP2.6. For instance, a recent crop model intercomparison study indicates strong negative effects from climate change on agricultural yields under RCP8.5 (Rosenzweig et al., 2014). In particular extreme daytime temperatures around 30°C have been identified to have large negative effects on crop yields (Porter et al., 2014). Lower yields could increase land requirements for agriculture and hence deforestation rates. Thus, negative climate impacts on agricultural yields might translate into detrimental effects on the terrestrial carbon balance. For a more comprehensive picture of possible land-use pathways under climate change, their implications for the terrestrial carbon cycle, and potential feedback to the climate system, future research should explore the interactions of these three dimensions under different RCPs.

Biophysical effects of land-use change on the climate system

Land-use changes, such as deforestation or afforestation, have not only biogeochemical (changes in carbon stocks) but also biophysical effects (changes in surface albedo) on the climate system (see chapter I, section 1.4.3). Since CO_2 is well mixed in the atmosphere, CO_2 emissions have a global impact on the climate system (Myhre et al., 2013). In contrast, changes in surface albedo have rather local impacts on the climate. A recent study with an earth system model indicates that afforestation triggers counteracting biogeochemical and biophysical effects (Davies-Barnard et al., 2014). CDR from the atmosphere due to large-scale afforestation results in a global biogeochemical cooling effect. At the same time, large-scale afforestation reduces the surface albedo, in particular in high latitude regions, leading to local biophysical warming effects. At the global scale, the biophysical warming effects offset the biogeochemical cooling effect. Thus, according to Davies-Barnard et al (2014), the net effect of afforestation is global warming, which is the opposite effect to that intended. This thesis focused on carbon stock changes due to large-scale afforestation (without analyzing the associated global temperature effects), while biophysical effects of afforestation on the climate have not been considered. Thus, the potential of afforestation for climate change mitigation might have been overestimated in this thesis. Potential net warming effects of large-scale afforestation in high latitudes have partially been addressed in chapter VI by prohibiting afforestation in these regions in the MAgPIE simulations.

Recycling of revenues from carbon pricing

The establishment of property rights for the disposal of CO_2 in the atmosphere would generate a rent, which could then be collected by pricing CO_2 emissions (Edenhofer et al., 2014b). If the land-use sector is included in such a carbon pricing mechanism, the costs of agricultural production likely increase due to additional costs for agricultural expansion into forests. While this is well represented in the MAgPIE model, the flow of money from the agricultural sector to a carbon market and finally to the entity that manages the atmosphere as a global common good is not represented in the MAgPIE model. Thus, revenues that accrue from carbon pricing cannot be recycled model internally for any other purpose. In the real world, however, revenues from carbon pricing could be used for a variety of activities, such as infrastructure build-up or financing redistribution polices. In particular the latter could be of importance with respect to potential impacts of land-based climate polices on food prices (see below under *Impacts of land-based climate polices on food prices*).

Forest-climate polices and the issue of permanence

With regards to afforestation and avoidance of deforestation, permanence is a crucial issue since only the permanent storage of sequestered carbon in vegetation and soil effectively removes CO_2 from the atmosphere. Thus, any process that threatens the existence of forests also jeopardizes the contribution of forest-climate policies to carbon mitigation. The MAgPIE model has no explicit representation of wildfires or insect outbreaks (e.g. bark beetle), which could release carbon from forests back to the atmosphere in the real world. Therefore, the mitigation potential of forest-climate policies might be overestimated to some degree in this thesis. Notwithstanding, the MAgPIE model accounts of anthropogenic land-use dynamics and their impacts on the terrestrial carbon balance. For instance, in the event of a falling carbon price it might become attractive at some point to quit an afforestation project, clear the forest and use the land instead for agricultural production.

Income and price elasticities of food demand

The food demand trajectory that is used in the MAgPIE model is calculated based on population and income projections (Bodirsky et al., n.d.). Hence, income effects on food demand are considered (income elasticity of food demand). In contrast, the current version of the MAgPIE model does not account for price effects on food demand (price elasticity of food demand). In the current version, model endogenous changes in food prices have no impacts on food demand, since food demand is exogenous to model. For example, potential food price increases due to competition for land under land-based mitigation cannot translate into food demand reductions. However, food demand is generally price inelastic since food is a necessity good (Hertel, 2011). The price elasticity of food demand has been estimated at -0.08 for the United States (Seale et al., 2003), i.e. food demand decreases by just 0.08% if food prices increase by 1%. For low-income countries, price elasticities are substantially higher, e.g. -0.26 in Tanzania, but still far away from unit elasticity (-1), which would imply a proportional change of prices and demand. Thus, the potential of land-based carbon mitigation might have been underestimated to some extent in this thesis due the missing responsiveness of food demand to changes in food prices in the current version of the MAgPIE model. For instance, sensitivity analysis in chapter II with a demitarian food demand scenario that cuts the consumption of livestock products in half showed 23% lower land-use change emissions.

Impacts of land-based climate polices on food prices

This thesis showed that land-based measures for the mitigation of CO_2 emissions, such as large-scale afforestation, avoidance of deforestation and bioenergy deployment, would require an intensification of agricultural production. The costs for intensification in the agricultural sector, such as investments in yield-increasing technological change, might increase food prices. In this thesis, impacts of land-based climate polices on food prices have not been analyzed. However, information on food price dynamics is important for evaluating the implications of land-based climate polices on food security. The following paragraph provides a brief literature review of food price dynamics in the context of land-based climate polices.

"Restrictions to agricultural expansion due to forest conservation, increased energy crop area, afforestation and reforestation may increase costs of agricultural production and food prices." (Smith et al., 2014, p. 841)

In an IAM study, excluding 99% of non-commercial forests from available land for agricultural expansion had only small effects on food prices (10% increase until 2095), while excluding 99% of natural ecosystems more than doubled food prices (260% increase until 2095) (Calvin et al., 2014). There is indication that bioenergy production consistent with low GHG stabilization targets has only minor effects on food prices, if land-use change is not regulated or if the feedstock used for bioenergy production originates from forest residues (Lotze-Campen et al., 2014). According to a recent study with several economic land-use models of global coverage, 100 EJ bioenergy production in 2050 increases food prices on average by about 5% compared to a reference scenario without bioenergy (Lotze-Campen et al., 2014). In contrast, climate impacts on crop yields in a high emissions scenario increased food prices by about 25% until 2050. However, if forests are excluded from the available land for agricultural expansion, e.g. due to sustainability criteria, the impact of bioenergy production on food prices is much stronger (increase of 82% in Africa, 73% in Latin America and 52% in Pacific Asia until 2095) (Popp et al., 2011a). Large-scale afforestation could more than double food prices throughout the 21st century due to competition for land (Calvin et al., 2014; Wise et al., 2009).

From the above literature review, two important insights can be gained. First, the magnitude of food price shifts strongly depends on the type of land-based climate policy. Second, the interactions between land-based mitigation options matter. For instance, avoidance of deforestation has minor impacts on food prices, while comprehensive land-use protection or large-scale afforestation more than double food prices in the course of the 21st century. Impacts on food prices due to bioenergy production are small if land-use change is unregulated but strong if forest is protected. A rise in food prices could have negative impacts on food security. Thus, some land-based climate polices, e.g. afforestation, might require redistribution policies to attenuate such adverse side effects.

Regarding future studies with the MAgPIE model it seems scientifically highly relevant to analyze food price effects of land-based climate polices. However, it should be considered that in the current version of the MAgPIE model the reactions of food markets to changes in food prices are not represent since food demand is exogenous to the model (see above under *Income and price elasticities of food demand* for details).

Capital stock and monetary flows

In economic theory, capital is everything that helps people make things. For instance, a computer helps PhD students writing their thesis and hence can be considered as capital. Buying additional memory can increase the productivity of the computer. In this context, the differentiation between stocks and flows is crucial. While capital is a stock that can build-up or deplete (the computer), investments are monetary flows that cause changes in capital stocks (buying additional memory). The MAgPIE model features a limited representation of capital stocks and monetary flows. Three examples: a) investments in land conversion increase the stock of cropland that can be used for crop production, b) investments in irrigation infrastructure increase the stock of irrigated area and hence the productivity of land, c) investments in R&D in the agricultural sector increase the stock of knowledge about agricultural practices that help to use agricultural land more efficiently. The calculus for such investments within the MAgPIE model is fully determined by the objective function, which is cost-minimization. However, the MAgPIE model has no closed accounting system for monetary flows, which implies that there is no budget constraint on investments. Thus, the monetary flows required for investments within the MAgPIE model are assumed to originate from exogenous and unconstrained sources. On the other hand, the MAgPIE model only undertakes investments that are cost-efficient, i.e. investments that reduce the overall global costs of agricultural production. Therefore, the missing budget constraint for investments should not lead to over-investment in the MAgPIE model. Furthermore, for the whole economy the overall importance of expenditures for agricultural R&D is small. In the 2000s (average from 2000 to 2009), global expenditures for agricultural R&D amounted to about

1% of agricultural income (Pardey et al., 2013), while agricultural income was about 3.5% of total income globally (World Bank, 2014).

Investments in yield-increasing technological change

According to chapters V and VI of this thesis, the combination of large-scale afforestation and bioenergy production requires about a tripling of current agricultural yields throughout the 21st century when food production is kept unaffected from potential interferences with land-based mitigation. Are such substantial yield increases in the agricultural sector realistic in the coming decades?

Between 1961 and 2007, global corn yields increased by a factor of 2.5 or on average by 2% per year, mainly due to the green revolution (Edgerton, 2009; Khush, 1999). In particular in regions that have seen considerable yield increases in recent decades, such as Europe or the USA, it might turn out difficult to maintain historic yield growth rates since the land-use intensity in these regions is already today relatively high (Dietrich et al., 2012). Moreover, the marginal costs of advances in agricultural productivity likely scale with the level of agricultural productivity. Thus, declining returns on investments in R&D in the agricultural sector might be another factor that lower yield growth rates in the future. While this line of argument holds true for conventional food crops, for dedicated lignocellulosic bioenergy crops the situation is different since R&D for advances in bioenergy crop yields has just started (Głowacka, 2011). For instance, the current yield of miscanthus is expected to double until 2030 (Chum et al., 2011). The MAgPIE model accounts for differences in food-crop-based land-use intensity and declining returns on investments of yield-increasing technological change between world regions (Dietrich et al., 2012; Dietrich et al., 2014) but does not differentiate between yield-increasing technological change for food and bioenergy crops. Thus, the MAgPIE model is rather pessimistic regarding the costs that accrue for advances in bioenergy crop yields. On the other hand, investments in yield-increasing technological change are driven by the revenues from land-based CDR, such as large-scale afforestation. However, as a partial equilibrium model, MAgPIE does not account for interactions with other economic sectors (see below for details). In the real world, the generation of negative emissions due to large-scale afforestation might reduce the market price for emission allowances and hence the revenues for CDR. In consequence, this could reduce investments in yield-increasing technological change in the agricultural sector. Such market feedback effects have not been accounted for in this thesis. Thus, the economic incentives for investments in R&D in the agricultural sector leading to yield increases might have been overestimated to some degree in this thesis.

Partial equilibrium model of the agricultural sector

MAgPIE is a partial equilibrium model of the agricultural sector. In contrast to a general equilibrium model that accounts simultaneously for various sectors of the economy that are mutually interdependent, the MAgPIE model assumes that prices and quantities in all other sectors of the economy are constant (ceteris paribus) and unaffected from the agricultural sector. This has in particular implications for CDR through large-scale afforestation (chapters V and VI). In the absence of an economy-wide carbon market in the MAgPIE model, it is implicitly assumed that all generated carbon credits from afforestation can be sold immediately for an exogenously given carbon price. In the real world, however, an increased supply of carbon allowances likely reduces the carbon price at the global carbon market, which in turn could lower the demand for CDR through afforestation. The consideration of such market feedback effects on the carbon price and hence on the level of afforestation was beyond the scope of this thesis.

Another implication of the partial equilibrium approach used in this thesis concerns the level of bioenergy demand. Like carbon prices, bioenergy demand is exogenous to the MAgPIE model (an exception from this is chapter V, in which carbon prices serve as incentive for bioenergy use with CCS in the model simulations). Hence, model endogenous changes in bioenergy supply prices have no impacts on bioenergy demand in the MAgPIE model. In the real world, however, large-scale afforestation as reported in chapter VI might increase bioenergy supply prices due to competition for land. As a result, bioenergy demand could decrease, which would leave more land resources available for afforestation. On the other hand, an increased supply of carbon allowances from CDR through afforestation might reduce carbon prices (see above), which in turn might have feedbacks on both, bioenergy deployment as well as afforestation. Besides competition for land with afforestation, bioenergy deployment might be also affected by polices that control land-related GHG emissions (chapter III) or regulate water usage for bioenergy production (chapter IV). For instance, chapter III showed that bioenergy supply prices increase non-linearly with bioenergy demand under pricing of land-use change emissions from deforestation. Furthermore, chapter IV indicates that the prohibition of irrigated bioenergy production increases bioenergy supply prices. The consideration of supply and demand responses in the bioenergy market to such changes in bioenergy supply prices was beyond the scope of this thesis.

4 Outlook

The final section of this thesis gives an outlook how some of the methodological limitations identified in the previous section could be addressed in future model development and application.

Extension of the REMIND-MAgPIE coupling framework by afforestation

This thesis investigated the potential contribution of the global land system to climate change mitigation in the 21st century by using the spatially explicit economic land-use optimization model MAgPIE. The analyzed land-based climate polices in this thesis consist of sets of 2nd generation bioenergy demand and GHG price trajectories, which have been derived from earlier studies with the energy-economy-climate model REMIND. As highlighted in the above limitations section, bioenergy demand and GHG prices are exogenous to the MAgPIE model, which implies that potential impacts of land-based mitigation on the bioenergy and carbon markets as well as feedbacks from these markets to the land system are not accounted for. The energy-economy-climate model REMIND can be coupled to the land-use model MAgPIE to account for economy-wide price and quantity effects of bioenergy and GHG emissions. However, the REMIND-MAgPIE coupling framework does currently not include large-scale afforestation as CDR option. The following gives an outlook how the REMIND-MAgPIE coupling framework could be extended by afforestation. After a brief summary of the current REMIND-MAgPIE coupling framework, two different approaches for integrating afforestation are presented. The *simple* and the *sophisticated* approach differ fundamentally in methodology and both have their pros and cons.

REMIND is a global multi-regional general equilibrium model covering interactions between the energy system, the economy and the climate system. MAgPIE is a global multi-regional partial equilibrium model of the agricultural sector with spatially explicit representation of land-use dynamics. The coupling of REMIND and MAgPIE establishes an integrated assessment modeling framework for the analysis of climate change mitigation polices throughout the 21st century (Klein, 2014). The soft coupling is performed through exchange of price and quantity information on bioenergy and GHG emissions. First, REMIND calculates initial bioenergy demand and GHG prices based on an emulator of MAgPIE, which includes bioenergy supply prices for various bioenergy demand scenarios (bioenergy supply curves, see chapter III). Next, bioenergy demand and GHG prices are handed over to MAgPIE, which derives shadow prices for bioenergy, and associated GHG emissions from land-use and land-use change. In turn, REMIND adjusts bioenergy demand and GHG prices according to its objective function (welfare maximization), the availability of technologies (e.g. CCS) and the chosen climate target (e.g. 450 ppm CO_2eq in 2100). The process is iterated until price and quantity information on bioenergy and GHG emissions are consistent, i.e. until the changes between iterations are sufficiently small.

The *simple* approach of integrating afforestation in the REMIND-MAgPIE coupling framework consists of activating afforestation in the MAgPIE version that is used in the coupling with REMIND. In this setup, MAgPIE would decide about the quantity of afforestation based on the carbon price provided by REMIND, and the direct and indirect costs associated with afforestation within the land-use sector. REMIND would decide about bioenergy use based on the bioenergy supply price provided by MAgPIE, and the direct and indirect costs associated with bioenergy deployment in the energy sector. From a theoretical perspective this division of decision-making between REMIND (bioenergy) and MAgPIE (afforestation) seems fine: bioenergy supply prices from MAgPIE (marginal costs of bioenergy production) reflect the competition for land between various land-related activities, such as bioenergy production and afforestation, while carbon prices from REMIND (marginal costs of mitigating CO_2 emissions) reflect the competition between various mitigation options (including bioenergy with CCS) in the energy sector. However, this division of decision-making between REMIND and MAgPIE does not account for a potential cross-price elasticity between afforestation and bioenergy. For instance, increasing bioenergy prices could increase demand for afforestation (substitute for CDR from bioenergy with CCS). Since MAgPIE does not consider bioenergy prices as input, it is not capable of adjusting afforestation to changes in bioenergy prices. Likewise, REMIND cannot adjust bioenergy demand to changes in afforestation costs, since it does not have information on afforestation costs. This missing cross dependency between afforestation and bioenergy in the *simple* approach could prevent the coupled REMIND-MAgPIE system from convergence due to cycling between low bioenergy / high afforestation and high bioenergy / low afforestation.

The idea of the *sophisticated* approach is to consider potential cross dependencies between afforestation and bioenergy. For instance, the current REMIND-MAgPIE coupling framework with bioenergy supply curves could be supplemented by afforestation supply curves derived using MAgPIE, with the aim to inform REMIND additionally about the level of CDR associated with afforestation under various carbon price scenarios. Accounting for interactions between afforestation and bioenergy in such supply curves strongly increases the computational effort. Currently, 73 bioenergy demand scenarios are used for deriving bioenergy supply curves with MAgPIE (see chapter III). If these 73 bioenergy demand scenarios were combined with 73 carbon price scenarios, more than 5000 MAgPIE runs would be required. Besides this huge computational effort, deriving afforestation supply curves comes along with a further complication since CDR from afforestation happens not at a particular point in time but over several decades. A ten-year time step in MAgPIE includes only the initial part of CDR from afforestation that happens within these ten years. All negative emissions that originate from this investment in afforestation at a particular carbon price but occur beyond the initial period are counted towards the respective future time steps. Hence, afforestation supply curves may show CDR at a particular carbon price although no additional land is required for generating these negative emissions. In other words, afforestation supply curves derived by MAgPIE only partially reveal at what carbon price the land requirements for afforestation change. Thus, the combination of bioenergy and afforestation supply curves derived by MAgPIE may not be sufficient to inform REMIND about the competition for land between afforestation and bioenergy, and its implications for bioenergy prices. In summary, the long-term character of afforestation as CDR option complicates the accounting for potential cross dependencies between afforestation and bioenergy in the REMIND-MAgPIE coupling framework.

Accounting for the net contribution of afforestation to climate change mitigation

As highlighted in the limitations section, this thesis did not provide temperature and radiative forcing effects associated with CDR from afforestation. Moreover, changes in surface albedo due to afforestation and their impacts on the climate system were disregarded. For future research, carbon stock gains from afforestation, derived by the economic land-use model MAgPIE, could be processed with the Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC) (Meinshausen et al., 2011) to obtain the associated biogeochemical temperature and radiative forcing effect. In addition, following the methodical approach of Davies-Barnard et al (2014), the land-use patterns derived by MAgPIE could be processed with an earth system model to obtain the biophysical temperature effects of surface albedo changes owing to afforestation. Finally, the sum of biogeochemical and biophysical temperature effects would provide a more comprehensive picture of the net contribution of large-scale afforestation to climate change mitigation.

The above post-processing approach allows identifying the global net cooling effect of afforestation activities that disregard temperature effects of surface albedo changes in the decision-making process. Based on hypothetical land-use pathways, such as full deforestation or full afforestation of the global land surface, earth system models can provide spatially explicit information on the net cooling effect of afforestation (Davies-Barnard et al., 2014). A further step for assessing the economic mitigation potential of afforestation could be the integration of such information into the decision-making process for afforestation in the MAgPIE model. In this setup, the MAgPIE model would not only optimize land-use patterns with respect to agricultural production costs and terrestrial carbon sequestration but also with respect to surface albedo. The general prohibition of afforestation in high latitude regions (above 50 degree North and South) in the MAgPIE simulations of chapter VI is a first step into this direction.

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Nomenclature

AFOLU	Agriculture, forestry and other land use
BECCS	Bioenergy with CCS
CCS	Carbon Capture and Storage
CDR	Carbon dioxide removal
CH_4	Methane
CO_2	Carbon dioxide
CO_2eq	CO_2 equivalent
GCM	Global Circulation Model
GHG	Greenhouse gas
IAM	Integrated assessment model
IPCC	Intergovernmental Panel on Climate Change
LPJmL	Lund-Potsdam-Jena model for managed Land
LULCC	Land-use and land-cover change
MAgPIE	Model of Agricultural Production and its Impacts on the Environment
MRV	Monitoring, Reporting and Verification
N_2O	Nitrous oxide
PIK	Potsdam Institute for Climate Impact Research
RCP	Representative Concentration Pathway
REDD	Reducing Emissions from Deforestation and Forest Degradation
SPA	Shared Policy Assumptions
SSP	Shared Socio-economic Pathway

Statement of contributions

Chapter II: Land use protection for climate change mitigation

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A. Popp designed the overall study; F. Humpenöder and M. Bonsch handled the MAgPIE model runs. A. Popp wrote the manuscript with important contributions from F. Humpenöder, B.L. Bodirsky, C. Müller and M. Bonsch; A. Popp, F. Humpenöder, M. Bonsch and B.L. Bodirsky analyzed results; F. Humpenöder, I. Weindl, B.L. Bodirsky, M. Bonsch, J.P. Dietrich, A. Popp, M. Stevanovic, A. Biewald and H. Lotze-Campen contributed in developing and improving the MAgPIE model; C. Müller and S. Rolinski provided biophysical input data from LPJmL; all authors discussed and commented on the manuscript.

Chapter III: The global economic long-term potential of modern biomass in a climate-constrained world

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D. Klein is responsible for the conceptual design, handling and writing of the article; D. Klein developed the data processing and fitting framework for constructing the bioenergy supply curves; D. Klein designed and performed the underlying MAgPIE runs and wrote the paper with input from F. Humpenöder (description of the MAgPIE model and some figures in the SOM) and with revisions by the co-authors, particularly N. Bauer and A. Popp; F. Humpenöder and J.P. Dietrich gave substantial support by handling MAgPIE-internal issues that occurred in the preparation phase and they also contributed to parts of the data analysis and discussion of the paper. F. Humpenöder, J.P. Dietrich, D. Klein, B. Bodirsky, M. Bonsch, A. Popp and H. Lotze-Campen contributed in developing and improving the MAgPIE model; all authors discussed and commented on the manuscript.

Chapter VI: Trade-offs between land and water requirements for large-scale bioenergy production

Status: published in Global Change Biology (GCB) Bioenergy, November 2014

M. Bonsch and A. Popp designed the overall study with important contributions by F. Humpenöder; M. Bonsch handled the MAgPIE model runs; M. Bonsch, F. Humpenöder and J.P. Dietrich analyzed results; M. Bonsch wrote the manuscript with important contributions from F. Humpenöder, A. Popp and J.P. Dietrich; M. Bonsch, F. Humpenöder, J.P. Dietrich, S. Rolinski, A. Biewald, I. Weindl, M. Stevanovic, B. Bodirsky, H. Lotze-Campen, and A. Popp contributed in developing and improving the MAgPIE model; all authors discussed and commented on the manuscript.

Chapter V: Investigating afforestation and bioenergy CCS as climate change mitigation strategies

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F. Humpenöder, A. Popp and J.P. Dietrich designed the overall study; F. Humpenöder handled the MAgPIE model runs; F. Humpenöder and J.P. Dietrich analysed results; F. Humpenöder wrote the manuscript with important contributions from A. Popp, B.L. Bodirsky and M. Bonsch; C. Müller provided biophysical input data from LPJmL; F. Humpenöder, M. Bonsch, I. Weindl, J.P. Dietrich, D. Klein, B.L. Bodirsky, M. Stevanovic, H. Lotze-Campen and A. Popp contributed in developing and improving the MAgPIE model; all authors discussed and commented on the manuscript.

Chapter VI: Land-use and carbon cycle responses to moderate climate change: implications for land-based mitigation?

Status: submitted to Environmental Science & Technology, December 2014

F. Humpenöder and A. Popp designed the overall study; F. Humpenöder handled the MAgPIE model runs, analyzed results and wrote the manuscript with important contributions from A. Popp, B.L. Bodirsky and C. Müller; C. Müller provided biophysical input data from LPJmL for 5 GCMs; M. Stevanovic and F. Humpenöder prepared the LPJmL data for use in MAgPIE; F. Humpenöder, M. Stevanovic, M. Bonsch, B.L. Bodirsky, I. Weindl, J.P. Dietrich, A. Popp, H. Lotze-Campen and A. Biewald contributed in developing and improving the MAgPIE model; all authors discussed and commented on the manuscript.

Tools and Resources

The results of this thesis rely on model-based computer simulations. A number of tools and resources were used for preparing input data, source code management, running the model simulations, and analyzing and visualizing the results. This chapter lists these tools and resources.

Modeling

Technically, MAgPIE is a mathematically programming model that is written in GAMS[6] and uses the CONOPT[7] solver.

Computational resources

The model simulations were performed on PIK's high performance cluster computer[8].

Data processing

The statistical programming software R[9] was used for the pre-processing of input data (aggregation and transformation) and the post-processing of output data (graphs, tables, validation).

Source code management

The source code of the MAgPIE model and the data processing scripts were managed using the Subversion[10] version control system.

Typesetting

This document was prepared with Microsoft Word 2011[11], Microsoft Word 2013[12] and Adobe Acrobat X Pro[13].

Literature management

Zotero[14] was used for literature management and generating the bibliography of this thesis.

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[6] http://www.gams.com
[7] http://www.gams.com/docs/conopt3.pdf
[8] https://www.pik-potsdam.de/services/it/hpc
[9] http://www.r-project.org
[10] http://subversion.apache.org
[11] http://www.microsoft.com/mac/word
[12] http://products.office.com/word
[13] http://www.adobe.com/Acrobat_X
[14] https://www.zotero.org

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