Economic losses from tropical cyclones in the USA – An assessment of the impact of climate change and socio-economic effects

vorgelegt von

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Abstract

Losses from weather-related natural catastrophes are increasing. The underlying causes of this trend are already known. They include, on the one hand, socio-economic factors, in particular the increase in population and wealth, and also increased settlement in the regions exposed to natural catastrophes. A further role is played by changes in the frequency and intensity of the weather extremes themselves, whether as part of natural climate variability, or as the result of anthropogenic climate change. The extent to which anthropogenic climate change has already influenced the trend in losses, or will influence it in the future, has yet to be clarified. For this, the portion of the increase in losses due to socio-economic and climate-related factors still needs to be reliably quantified.

This doctoral thesis will provide additional components to reduce the uncertainties surrounding the role of socio-economic and climate-related factors in loss trends. In particular, it will focus on two questions:

- Is it possible to quantify more precisely the influence that climate change (both anthropogenic and natural) has on the increase in losses already?
- What losses may be expected in the medium and long term, if we make allowance for both climate-related and socio-economic trends in the future?

By way of example, these issues are analysed in three studies for losses from North Atlantic tropical cyclones in the USA.

The first study adjusts the loss data for the socio-economic effects it contains and then subjects the data to a trend analysis. Any remaining trend could no longer be explained as being due to socio-economic developments. Instead, it would point to the influence of climate change. The basis for the adjustment for socio-economic effects is a new approach whereby the loss data are adjusted according to the changes in capital stock at risk. The second study examines how sensitive storm losses are to changes in socio-economic and climate related factors, and looks at the trends in these factors over the period 1950–2005. From this, conclusions are drawn on the shares the different factors have in the overall trend. Both studies determine a climate-related influence. However, it is not possible to directly attribute losses to anthropogenic greenhouse gas emissions. By way of a summary from the first two studies, the hypothesis is proposed that it is at least probable that part of the loss increase stems from anthropogenic climate change.

The third study addresses the second of the two questions above and simulates the average annual loss that would result following assumptions about the impact of anthropogenic climate change and about future socio-economic trends. It shows that the principal loss driver in future will be the increase in wealth in the regions at risk from storms. However, anthropogenic climate change will also lead to a significant increase in losses.

Keywords: anthropogenic climate change, future loss simulation, insurance, socio-economic impact, loss trends, Monte Carlo simulation, natural catastrophes, natural climate variability, stochastic modeling, storm damage function, tropical cyclones.

Zusammenfassung

Die Schäden durch wetterbedingte Naturkatastrophen nehmen zu. Die dieser Entwicklung zugrundeliegenden Ursachen sind bekannt. Es sind dies einerseits soziökonomische Faktoren, vor allem die Zunahme der Bevölkerung und des Wohlstandes sowie die verstärkte Besiedlung der durch Naturgefahren bedrohten Gebiete. Daneben spielen Veränderungen in der Häufigkeit und der Intensität der Wetterextreme selbst eine Rolle, sei es aufgrund natürlicher Klimavariabilität oder infolge des anthropogenen Klimawandels. Unklarheit herrscht bislang, wie stark der anthropogene Klimawandel die Entwicklung der Schäden bereits beeinflusst beziehungsweise in Zukunft beeinflussen wird. Eine hierfür notwendige belastbare Quantifizierung des Anteils der sozioökonomischen und klimabedingten Faktoren an der Schadenentwicklung steht noch aus.

Die Dissertation liefert weitere Bausteine, um die Unsicherheiten zu reduzieren, die hinsichtlich der Rolle der sozioökonomischen und klimabedingten Faktoren an der Schadenentwicklung bestehen. Sie orientiert sich dabei an zwei Fragen:

- Lässt sich der bisherige Einfluss des (anthropogenen wie natürlichen) Klimawandels auf die Zunahme der Schäden quantitativ näher bestimmen?
- Mit welchen Schäden muss mittel- bis langfristig gerechnet werden, wenn sowohl zukünftige klimabedingte wie sozioökonomische Entwicklungen berücksichtigt werden?

Diese Fragen werden in drei Studien exemplarisch für Schäden nordatlantischer tropischer Wirbelstürme in den USA untersucht.

Die erste Studie bereinigt die Schadendaten um die in ihnen enthaltenen sozioökonomischen Effekte und unterzieht sie anschließend einer Trendanalyse. Ein verbleibender Trend wäre nicht mehr mit den sozioökonomischen Entwicklungen zu erklären. Vielmehr würde er auf den Einfluss des Klimawandels hindeuten. Grundlage für die Bereinigung um die sozioökonomischen Effekte ist ein neuer Ansatz, mit dem die Schadendaten anhand der Änderungen des sturmgefährdeten Kapitalstocks angepasst werden. Die zweite Studie untersucht, wie sensibel Sturmschäden auf Änderungen der sozioökonomischen Faktoren und der klimabedingten Faktoren reagieren und wie sich diese Faktoren im Zeitraum 1950–2005 entwickelt haben. Daraus zieht sie Rückschlüsse auf die Anteile der Faktoren an der Gesamtentwicklung. Beide Studien stellen einen klimabedingten Einfluss fest. Eine direkte Zuordnung der Schäden auf die anthropogenen Treibhausgasemissionen ist jedoch nicht möglich. Als Fazit aus den ersten beiden Studien wird die Hypothese aufgestellt, dass es aber zumindest wahrscheinlich ist, dass ein Teil des Schadenanstiegs auf den anthropogenen Klimawandel zurückgeht.

Die dritte Studie wendet sich der zweiten Frage zu und simuliert den mittleren Jahresschaden, wie er sich unter Annahmen über die Auswirkungen des anthropogenen Klimawandels als auch der zukünftigen sozioökonomischen Entwicklungen ergibt. Sie zeigt, dass auch in Zukunft die Wohlstandszunahme in den sturmgefährdeten Gebieten der wesentliche Schadentreiber sein wird. Aber auch der anthropogene Klimawandel wird zu einer nicht unerheblichen Zunahme der Schäden führen.

Schlagworte: anthropogener Klimawandel, Monte-Carlo-Simulation, natürliche Klimavariabilität, Naturkatastrophen, Schadensimulation, Schadentrends, sozioökonomischer Einfluss, stochastische Modellierung, Sturmschadenfunktion, tropische Wirbelstürme, Versicherung.

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1 Introduction

1.1 Motivation and aim

Over the last decades, losses from weather-related natural catastrophes have risen significantly. A sizable portion of these losses has occurred in the USA as the result of tropical cyclones (see Figure 1.1). Total global losses from weather-related natural catastrophes in 2008 amounted to 123 billion US$ (2008 values), of which 38 billion dollars were losses from cyclones in the USA. This corresponds to a 31% share of the total. For the two extreme loss years of 2004 and 2005, the figures were as much as 49% and 73% respectively.

The main causes of the increase in losses from tropical cyclones in the USA, and from weather-related natural catastrophes in general, are known. They can be divided into three groups (see Figure 1.2). The first group comprises factors that influence the frequency and intensity of weather extremes. The second group encompasses factors influencing loss susceptibility and the material assets at risk from weather extremes (exposure). The first group of such factors consist of "climate-related factors". These include influences such as anthropogenic climate change and also natural climate variability. The second group are "socio-economic factors", resulting from changes in population and wealth, and from greater settlement in the regions threatened by natural hazards. This group also includes the change in vulnerability to weather extremes and the concentration of people and assets in highly exposed conurbations (cf. Berz, 2004). Loss statistics are also influenced by factors that stem from changes in the perception and quantitative valuation of natural catastrophes (data reporting changes).

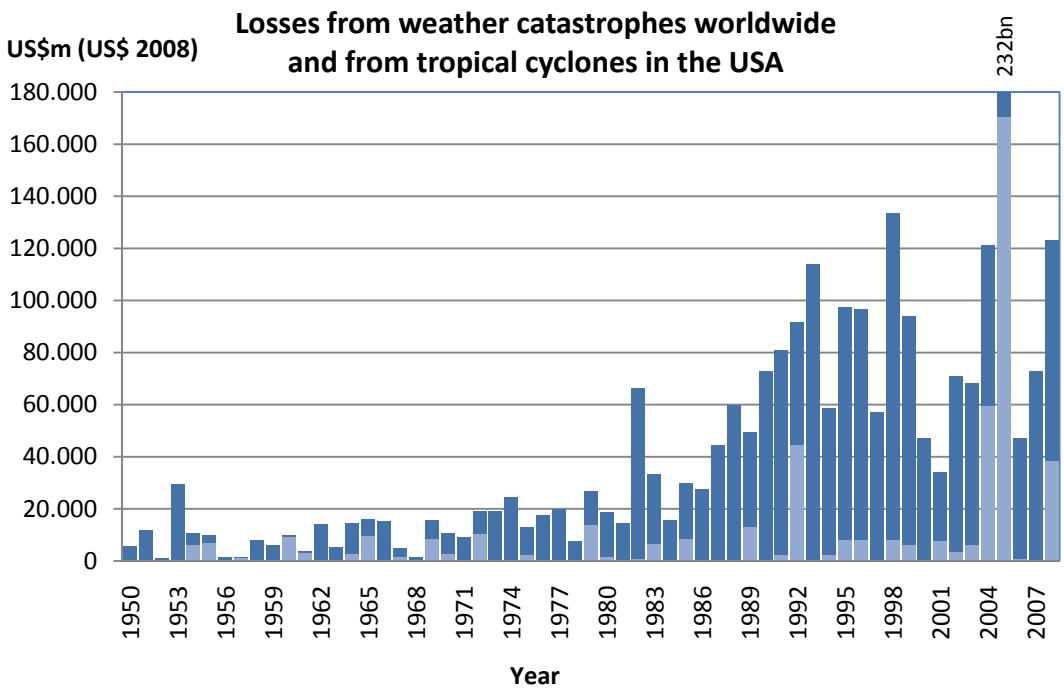

Figure 1.1: Worldwide losses from weather-related natural catastrophes, and losses from tropical cyclones in the USA in the years 1950–2008 in millions of US$ (2008 values) (source: Munich Re, NatCatSERVICE®, 2009; graphic: author).

Socio-economic trends and anthropogenic climate change will lead to further loss increases in the future. The number of people and the total value of material assets in the affected regions of the USA must both be expected to increase. These trends have been the principal drivers up to now of the observed rise in losses (cf. IPCC, 2007b) and are likely to remain so in the future. There is uncertainty about the influence of anthropogenic climate change. Should its effects be discounted in view of the dominant role played by population growth and greater wealth (cf. Pielke Jr. et al., 2005), or does anthropogenic climate change play a much more significant role, whose effects are exacerbated by socio-economic factors (cf. Mills, 2005)? The portion of climate- and socio-economically-related losses in terms of the overall trend is still unclear. It is therefore important to understand more precisely the influence of the different groups of factors (cf. Mills and Roth, 2005).

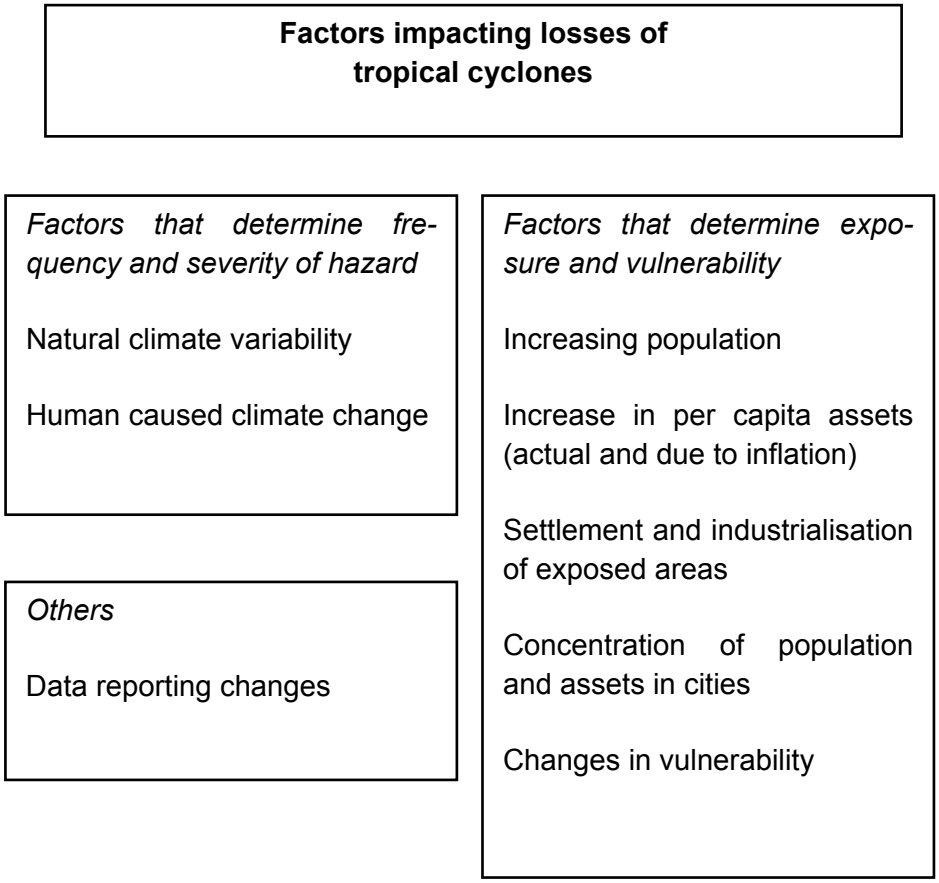

Figure 1.2: Principal factors that influence the increase in losses from tropical cyclones.

If anthropogenic climate change results in a significant change in the trend in losses, the insurance industry would be one of the first sectors to be seriously affected. Accordingly, insurance companies are interested in researching and mitigating anthropogenic climate change (cf. Allianz Group and WWF, 2005, Lloyd‘s, 2006 and also Geneva Association, 2009). According to Berz (2004), insurance companies try to “play it safe” with their risk assessment. Although the global balance of risks still works effectively, allowing insurers to guarantee the insurability of catastrophe risks even in the long-term, they are worried that the rising loss trends could destroy the basis for determining premium prices. Premiums are by necessity one step behind losses. Insurers are also concerned that loss potentials could develop in highly ex-

posed regions that would push them to the limits of insurability (cf. also Diaz and Pulwarty, 1997). Even though the insurance industry has repeatedly demonstrated its ability in the past to adjust to a constantly changing risk environment, it would like to use its influence to ensure that unwelcome trends from anthropogenic climate change do not arise in the first place, by mitigating or even eliminating risk trends in good time (cf. Berz, 2004). However, a change in weather extremes is of significance for more people than just insurance companies. The latter merely pass on the effects of such a change to the general public, in the form of premium adjustments and risk selection (cf. Mills, 2005).

Socio-economic and climate-related losses have still not been satisfactorily quantified as a portion of the overall development (cf. Höppe and Pielke Jr., 2006). This task is considered difficult because of the available data quality, the stochastic nature of weather extremes, and the parallel influence of both groups of factors (cf. Diaz and Pulwarty, 1997, Höppe and Pielke Jr., 2006, Reinhart, 2004).

This is where the present paper has a contribution to make. It intends to provide additional components to reduce the uncertainties surrounding the role of socio-economic and climate-related factors in the loss development. This will make it easier to assess how relevant anthropogenic climate change is in relation to losses from weather extremes. The paper will focus on providing answers to two different questions:

- Is it possible to quantify more precisely the influence that climate change (both anthropogenic and natural) has on the increase in losses already?
- What losses may be expected in the medium and long term, if we make allowance for both climate-related and socio-economic trends in the future?

By way of example, the analyses focus on direct economic losses in the USA from North Atlantic tropical cyclones. The term “tropical cyclone” is used to designate storms with wind speeds of more than 63 km/h that form over the sea in the tropics. Depending on the region, they may be referred to as typhoons in the northwest Pacific, cyclones in the Indian Ocean and Australia, and hurricanes in the Atlantic and northeast Pacific. Pielke Jr. and Pielke Sr. (1997) provide a very good introduction to the scientific and societal dimensions of tropical cyclones in the USA. The justification for the focus of the doctoral thesis on losses in the USA is that particularly high losses occur there. This is a result of the high concentration of material assets in the regions threatened by storms. As Figure 1.1 illustrates, they account for a substantial portion of annual global losses from weather-related natural catastrophes. In addition, there are studies on storm losses in this region that can be used for comparison purposes. Furthermore, the availability of the required data is relatively good for the USA.

In this doctoral thesis, the term “climate change” is used as defined by the IPCC in its Fourth Assessment Report: “Climate change refers to any change in climate over time, whether due to natural variability or as a result of human activity” (IPCC, 2007b, 871). The doctoral thesis does not see itself in a position to make quantitative statements about the separate effects of natural climate variability and human activity. According to Höppe and Pielke Jr. (2006), this question is unlikely to be settled unequivocally in the near future. Nevertheless, the impact that climate change as a whole (due to both natural and anthropogenic forcings) has on loss trends is still worth looking at in more detail.

1.2 Current state of research

Kemfert and Schumacher (2005) establish that economics literature focuses on the cost of mitigating anthropogenic climate change, but pays little attention to the cost of climate change, in other words the losses resulting from a changing climate. This paper only examines losses from climate change, and of these losses, only losses from weather extremes. There are indications that changing patterns in weather extremes are a driver leading to the observed increase in losses from natural catastrophes (cf. Höppe and Pielke Jr., 2006). On the question of changing patterns of tropical cyclones, the IPCC states in its Fourth Assessment Report that

- there have been indications of an increase in the destructive force of storms in most of the ocean basins since the mid-1970s. The storms are tending to last longer and are more violent. This increase correlates very closely with the sea surface temperatures (SST).
- the number of severe storms, i.e. storms in hurricane categories 3–5 (on the Saffir-Simpson scale), is increasing worldwide. However, the total number of storms is falling slightly.
- for the North Atlantic, we can observe both an increase in the number and the intensity of the storms.

The IPCC also states that it is more likely than not that human activities play a role in these trends (cf. IPCC, 2007a, 2007b).

The aim of this paper is to establish in the first part whether a climate signal is apparent in the empirical loss data, and whether this allows conclusions to be drawn on the influence that anthropogenic climate change has had up to now. In order to do this, we first need to adjust the losses for the effects of inflation, and the growth in population and wealth. Otherwise, there will already be an upward trend in losses from socio-economic developments (cf. IPCC, 2007b, Miller et al., 2008). Pielke Jr. and Landsea (1998) were the first to present a groundbreaking approach called "Normalized Hurricane Damages" for such an adjustment to discount socio-economic factors in storm losses in the USA. The influence of population change is measured as the ratio of the population today to the population in the year of the storm. As the basis for the population figures, the authors use the worst-hit region. The influence of the change in wealth is ascertained as the ratio of current per capita wealth to the per capita wealth in the year of the storm. The adjusted loss is established by multiplying the inflation-adjusted loss by the factors for population change and change in wealth. This gives the loss under the standardised socio-economic conditions of a reference year.

Nordhaus (2006) adopts a different method of adjusting the loss data for socio-economic influences. He takes the ratio of the nominal storm losses to the gross domestic product (GDP) in the year of occurrence. The result represents the loss adjusted for the increase in GDP. Miller et al. (2008) also use GDP as an adjustment factor, because they are analysing global losses, and for many countries GDP is the only reasonably reliable factor available to measure the change in wealth.

Once the loss data has been adjusted for socio-economic changes, we can then perform trend analyses. Any remaining trend could no longer be explained by changes in population or wealth. Instead, it would

point to the influence of climate change. Pielke Jr. and Landsea (1998) analyse losses from North Atlantic tropical cyclones in the USA in the years 1925–1995 and conclude that there are no long-term trends (see also Pielke Jr., 2005). Pielke Jr. et al. (2008) arrive at the same result for the extended sample period 1900–2005. Pielke Jr. et al. (2003) carry out a comparable analysis for storm losses in Latin America, using GDP as the adjustment factor for wealth. This study likewise finds no indication of any relevant influence from anthropogenic climate change. For losses from tropical storms in India, Raghavan (2003) also concludes that economic and demographic factors are basically responsible for the rise in losses in the period 1971-2003 and not the increase in the frequency or intensity of the storms themselves (see also Pielke Jr. et al., 2006). The socio-economic factors, and not anthropogenic climate change, thus explain almost entirely the rise in losses from weather-related natural catastrophes. The same conclusion is reached by Brooks (2001) for tornado losses in the USA (in the period 1890–1999), by Baredo (2009) for flood damage in Europe, and by Crompton and McAneney (2008), who analyse insured losses from various weather extremes in Australia. Miller et al. (2008) analyse global losses, and for a variety of weather-related natural catastrophes. In the time series for adjusted global losses, they identify a remaining trend with an annual growth of 2%. This positive trend cannot be explained by socio-economic changes alone, and is cited by Miller et al. (2008) as the influence of climate change. However, statistically, this trend is only significant for the period 1970–2005. In addition, it is heavily influenced by the extreme years 2004 and 2005. Further mention should be made at this point of the work of Vranes and Pielke Jr. (2008). They analyse earthquake losses in the USA that are not influenced by climate (1900–2005). Once again, no trend is identified in the time series for adjusted earthquake losses.

Katz (2002a) performs statistical trend assessments applying loss data adjusted for tropical cyclones based on the database from Pielke Jr. and Landsea (1998) to a stochastic storm loss model. The author models the annual loss from tropical cyclones as the sum of the two random processes frequency and individual storm loss. He then uses this random total to quantify the components' shares in the variation in annual loss. He finds no indication of a systematic increase in either frequency or individual loss, and thus no signal of anthropogenic climate change in the losses.

Nordhaus (2006) depicts cyclone losses as a function of their intensity and vulnerability. Accordingly, the more intense the destructive force of the storm and the more vulnerable society is to disasters, the higher the losses. As mentioned, Nordhaus also uses loss data that are adjusted for socio-economic influences. Using an econometric model, he investigates the extent to which losses in the USA are affected by the maximum wind speed and time, with wind speed representing the storm intensity, and time the vulnerability. The findings indicate that storm losses are highly responsive to changes in maximum wind speed. Since Nordhaus perceives evidence of an increase in intensity in the North Atlantic (see also IPCC 2007a, 2007b), he thus provides an indication that climate change must be influencing the increase in losses.

The statements thus vary widely on the extent to which the empirical loss data reveal the influence of anthropogenic climate change. For those that indicate an influence, it remains to be seen whether the signal is due only to natural, or also to anthropogenic climate change. Based on the Nordhaus results, there are at least indications that anthropogenic climate change plays a part. According to Barnett et al. (2005), there is a connection between global warming and the warming of sea surface temperatures (see

also Elsner, 2006, Mann and Emanuel, 2006). The warming of the sea surface temperatures in turn correlates with the increase in storm intensity. This type of increase in storm intensity can at least be determined for the North Atlantic (cf. Emanuel, 2005, Hoyos et al., 2006, IPCC, 2007a, Webster et al., 2005). Finally, it is not possible at present to make sound quantitative statements about the influence from natural climate variability, or from global warming caused by human activity. According to Höppe and Pielke Jr. (2006), it will be some time before this question can be clarified in a satisfactory way.

The second part of the present paper is devoted to simulating future storm losses, such as may be expected from global warming and from future socio-economic trends. As already mentioned, economics literature focuses on the cost of mitigating climate change, but the cost of the effects of anthropogenic climate change, in other words the cost of inaction, is seldom addressed (cf. Kemfert and Schumacher, 2005). The preferred method of assessing the cost is currently using what are known as Integrated Assessment models (IA models). These models are based on an interdisciplinary approach that combines biophysical and socio-economic systems to make an integrated assessment of climate change (cf. WestLB, 2003). Stern et al. (2006) give an overview of the status of IA modelling (see also Kemfert, 2003, specifically on economic modelling of the cost of climate change, as well as Pearson and Fisher-Vanden, 1997). Models that incorporate costs from a changing climate do not make adequate allowance for losses from weather extremes (cf. Stern et al., 2006; for examples, see Smajgl, 2002, Springer, 2002, Tol, 2002a, 2002b). Losses from climate change are often included in the models as a function of temperature change. The principal justification for this rather simplified assumption of interdependencies is that they are not yet fully understood, as well as on the grounds of the lack of available data (cf. Bart and Hasselmann, 2005, as well as WestLB, 2003, Jöst, 2004, Nordhaus, 1994). In addition, simply a global loss function is sometimes implemented in the model (cf. Kemfert and Schumacher, 2005). Losses from weather extremes cannot therefore be adequately modelled. They represent only a portion of the losses from global warming. As well, they are very small-scale events, with corresponding regional losses. In earlier papers, losses from weather extremes were sometimes considered irrelevant in calculating the cost of climate change (cf. Nordhaus and Boyer, 2000). This view has changed ever since the impact of hurricane Katrina in 2005 (see Nordhaus, 2006). It has not been possible up to now to properly integrate weather extremes in the economic models used to assess the cost of climate change, so losses derived from them are simulated separately from these models.

As a rule, losses from weather extremes are simulated under the conditions that are expected at the end of the 21st century, assuming no climate protection measures are taken. This corresponds to the SRES A1 scenario of the IPCC (see Nakicenovic et al., 2000), describing the costs from weather extremes if no action is taken.

A useful presentation of the steps needed to simulate storm losses influenced by climate change can be found in Hallegatte (2007b). First of all, the influence that future greenhouse gas emissions have on climate needs to be simulated. This is done using a physical climate model. The result may be the change in sea surface temperatures for example. At the present time, climate models are unable to simulate small-scale effects such as storms. The change in the sea surface temperature, as determined by the climate model, therefore needs to be transferred to a further model that is only used to model storms. This model

determines the change in storms as a result of the changed climate parameters, in this case sea surface temperature. In principle, either statistical methods or physical storm models can be used for this. The former are based on statistical correlations obtained from historical data. One example could be the connection between sea surface temperature and storm intensity. The problem with statistical methods, however, is that it is not certain whether the correlations established today will continue to apply in the future. Physical models, on the other hand, are based on physical laws that will remain unchanged in the future (cf. Hallegatte, 2007b). There is currently a debate among storm experts on the extent to which sea surface temperature is actually the key factor for the change in storm intensity (see Bengtsson et al., 2007, Chan, 2006, Emanuel et al., 2008, Knutson and Tuleya, 2004, Vecchi et al., 2008, Wang and Lee, 2008). Parameters are obtained from the storm models to describe the change in the risk situation from storms (frequency, intensity) as a result of altered climate parameters. The third step is to transfer these parameters to loss models that simulate the change in loss resulting from the change in risk situation. Once again, either statistical methods or physical models can be used here. Statistical methods determine connections between observed storms and their losses, and use these as the basis for simulating future losses. Examples of future loss calculations using statistical methods can be found in Cline (1992), Fankhauser (1995), Hallegatte (2007a), Nordhaus (2006), Pielke Jr. (2007a) and Tol (1995). For storm losses in the USA by the end of the 21st century as a result of global warming, these studies calculate increases of between 50% (cf. Hallegatte, 2007a) and 100% (cf. Nordhaus, 2006, Stern et al., 2006). Physical loss models are mainly developed by risk consulting companies and are used by the insurance industry to calculate the necessary technical premium rate. The material assets at risk are used as the basis for the simulation of losses (for example in the form of the sum insured). Some of the problems with physical models stem from the fact that in many cases no data is available on material assets. Above all, it is difficult to make assumptions about their future value (cf. Hallegatte, 2007b). One example of a simulation of future storm losses that uses a physical model is the study carried out by the Association of British Insurers (ABI) (2005). The ABI calculates an average annual loss increase of 75% for the USA by the end of the century.

The additional losses specified in the studies listed only refer to additional losses from anthropogenic climate change. Only Pielke Jr. (2007a) and Pielke Jr. et al. (2000) simulate the additional overall losses that may occur as a result of the expected climate-related and socio-economic developments. The IPCC believes the increase in material assets will be a key factor in future storm losses (cf. IPCC, 2007b), but does not mention any papers that quantify the amount of losses from socio-economic change. The research focus on losses from anthropogenic climate change distorts the picture of the real loss driver, namely the increase in population and wealth. According to Pielke Jr. (2007a), there is a much greater potential for reducing losses from tropical cyclones by adaptation measures, rather than by reducing greenhouse gas emissions (mitigation measures). Up to now, there has been surprisingly little investigation of the overall future losses from weather extremes that are caused by both socio-economic and climate-related factors.

1.3 Structure of the doctoral thesis

The extent to which socio-economic factors or climate-related factors contribute to the increase in costs from weather extremes has not been adequately explained up to now. In addition, the cost from weather extremes is not an area that has been examined in great detail in research into anthropogenic climate change. This is clearly illustrated by the fact that only a small number of experts have focused on the subject. The present paper will provide additional components for this field of research by assessing and supplementing previous studies. This will help reduce the persisting uncertainties about the role that socio-economic and climate-related factors play already in the development of losses. The focus is firstly on the role that socio-economic and climate changes play in loss increases. The paper also examines the question of future costs from tropical cyclones, if both the effects of global warming and socio-economic trends are considered.

Using a cumulative approach, the doctoral thesis combines three different studies that investigate the above questions. Each of the studies addresses one or more of the approaches from the literature, expands on these and discusses the results arrived at in comparison with the results of the original studies. The doctoral thesis is divided into two sections, looking at the two problems in turn. The first two studies investigate the role played by socio-economic and climate-related factors in the loss trends. The third study looks at possible scenarios for future storm losses. The studies incorporated into the doctoral thesis have also been separately published in journals with a peer review process.

A new approach is presented in the first study that adjusts loss data for socio-economic trends (see also Schmidt, Kemfert, Höppe, 2009). In contrast to Pielke Jr. and Landsea (1998), this new approach uses the changes in capital stock at risk to adjust the losses from different years to a reference year. The capital stock at risk encompasses the value of material assets in the region affected by a storm. The approach is based on the assumption that a storm loss is basically a function of the intensity of the storm and the value of material assets affected by the storm. In contrast, Pielke Jr. and Landsea (1998) base their normalisation on the changes in population and per capita wealth. In the first study, losses from storms in the years 1950–2005 are uniformly raised to the socio-economic level of 2005 based on the trends in capital stock. The adjusted losses are then subjected to a trend analysis. Any remaining trend could no longer be explained by socio-economic developments. Instead, it would point to a change in the risk situation that is very probably caused by the influence of natural and anthropogenic forcings. The result shows that there is no statistically significant trend for the period 1950–2005, but that a clear trend is established for the period 1971–2005. During the latter period, there was an increase in the sea surface temperature in the North Atlantic and also in the intensity of North Atlantic tropical cyclones (cf. IPCC 2007a). Losses increased by an average of 4% per year, excluding the effects from inflation, population growth, and increased wealth. This increase can at least be interpreted as a consequence of natural climate variability, but is not a confirmation of the influence of anthropogenic climate change (cf. Schmidt, Kemfert, Höppe, 2009). However, such an influence is probable, since there are indications that the warming of the sea surface temperature in the North Atlantic since the 1970s cannot be explained solely by natural climate variability (cf. IPCC, 2007a, as well as Barnett et al., 2005; see also Elsner, 2006, Mann and Emanuel, 2006).

The second study presents an approach that examines the sensitivity of storm losses to changes in socio-economic and climate-related factors (see also Schmidt, Kemfert, Höppe, 2010). A loss function is developed that comprises the capital stock at risk from the storm, and the intensity with which the storm impacts these assets. The loss function normally only considers intensity, represented by the wind speed (for example Nordhaus, 2006). Unlike Nordhaus, the second study incorporates the socio-economic factors directly in the loss function. This avoids the need to exclude socio-economic factors from the loss data. A comparable method is described in Sachs (2007). The approach developed in the second study thus determines the elasticity of storm losses to a change in storm intensity, or to a change in the capital stock. The study shows that losses are much more sensitive to a change in storm intensity than to a change in the capital stock. Once the elasticity is known, it is at least possible to draw rough conclusions about what portion of the loss trends are due to socio-economic factors and the climate-induced storm intensity. For this purpose, the study examines the trends in capital stock and in storm intensity in the period 1950–2005. During this sample period, there was a much smaller change in capital stock than in climate-induced storm intensity. The result shows that the increase in losses from socio-economic changes is approximately three times higher than that due to climate-induced changes. Here again, the degree to which climate-induced changes are the result of natural climate variability, or of anthropogenic climate change, is open to discussion (cf. Schmidt, Kemfert, Höppe, 2010).

The first two studies therefore show that a climate signal can certainly be detected in the loss data. However, it is not possible to directly attribute the losses to greenhouse gas emissions resulting from human activity. The IPCC has stated that both the number and the intensity of storms in the North Atlantic are increasing, and that there is more likely than not a human component to these trends (cf. IPCC, 2007a, 2007b). As a summary from assessing the first two studies, we propose the hypothesis that it is at least probable that a portion of the loss increase stems from anthropogenic climate change.

The third study starts with the assumption that anthropogenic climate change influences storm losses. Unlike the first two studies, it focuses on future developments, simulating the expected increase in the average annual storm loss in the USA for the years 2015 and 2050 (see also Schmidt, Kemfert, Faust, 2009). Study number three thus concentrates on the second question addressed by this doctoral thesis. The simulation is based on assumptions about the future increase in wealth in the regions threatened by storms, taken into account by the change in material assets (capital stock), and on the trend in storm intensity. A stochastic model is used for the simulations that models the annual loss from the number of storms and the loss per storm. As mentioned in the section on the current state of research, some studies have been carried out into the future costs from tropical cyclones resulting from anthropogenic climate change. However, there are virtually no studies that simulate the costs of socio-economic development as well as the climate-related costs. Only Pielke Jr. (2007a) and Pielke Jr. et al. (2000) simulate these additional costs. Moreover, there is considerable uncertainty about the effects of global warming on storm losses, which is the reason why studies up to now have arrived at different results. The third study in this doctoral thesis provides a further simulation to that of Pielke Jr. (2007a) of the overall costs from future cyclones in the USA. An assessment of the total cost, for example, will allow conclusions to be drawn about the impending overall burden facing state-run and private insurance systems from insuring the natural hazard “tropical cyclone”. In addition, assessing the additional losses resulting from global warm-

ing will provide a further component to research the effects of anthropogenic climate change on losses from weather extremes. The study shows that the principal loss driver in future will be the increase in wealth in the regions affected by storms. At the same time, anthropogenic climate change will also lead to appreciable loss increases. The study further shows that the variations between the simulation results and the results of other studies, as well as between one study and another, can generally be explained by the assumptions made in each case. Any differences between the studies relating to the method applied do not play any relevant role. The study shows there is a need for further research to reduce the uncertainties relating to the change in frequency and intensity of storms, and to loss elasticity in relation to intensity (cf. Schmidt, Kemfert, Faust, 2009).

The three studies are each basically structured as follows. Following an introduction to the topics and a short overview of the current state of research, the underlying method and the data used are described. This is followed by a presentation and discussion of the results. The discussion focuses in particular on the underlying assumptions and the constraints that need to be considered when interpreting the results. The results are also compared with results from other papers and explanations are suggested for diverging results. The studies each conclude with a summary that brings together the principal results and the constraints that need to be considered. In addition, the results are interpreted in terms of their significance for the insurance of the natural hazard “tropical storm”. The three studies build on one another, with the result that some content may be repeated in places.

2 Data and data sources[1]

A database for tropical cyclones was used for the three studies. For the period 1950–2005, the database includes 131 North Atlantic storm events that resulted in losses on the US mainland. The following information is available for each of the events:

- name of the storm and the date of its landfall,
- capital stock at risk (material assets) in US$ after adjustment for inflation (2005 values),
- recorded maximum wind speed at landfall in knots (kt)[2],
- direct material damage caused by the storm in US$ after adjustment for inflation (2005 values).

2.1 Data on the capital stock at risk

In order to determine the capital stock at risk from the storm, we first need to specify the region believed to be affected. In this paper, the affected region covers all counties in the USA in which the storm caused material damage. It is ascertained from what is known as the wind field. This gives an areal representation of the storm and covers the region in which a specified wind speed was exceeded. In our case, the wind field covers a region in which the storm was still classified as a "tropical storm", with a wind speed of at least 63 km/h (see Figure 2.1 for an example). Appreciable damage results from this level of wind speed. The Storm Track Dataset of the National Oceanic and Atmospheric Administration was used as the basis for calculating the wind fields (cf. NOAA Coastal Services Center, http://maps.csc.noaa.gov/hurricanes/download.html).

To ascertain the capital stock in the relevant counties, we use a geographic information system (GIS), combining the wind field with a map of the US counties (see Figure 2.2). The map indicates the amount of capital stock in the individual counties in the year of the storm, and in 2005.

Annual estimates of US capital stock are presented in the form of national figures for fixed assets and durable consumer goods. However, details of fixed assets and consumer durables are not available for individual states or countries (according to a written reply from the Bureau of Economic Analysis on 23.08.2006). We have accordingly estimated time series for capital stock in the individual US counties and entered them in a database. The database comprises all US counties located in the area affected by North Atlantic cyclones. Capital stock details are therefore available for each of these 1756 counties for the period 1950 to 2005. Table 2.1 lists the US states where the counties are situated. The capital stock is estimated by taking the number of housing units and their mean value after adjustment for inflation in

[1] This chapter is based on publications in Regional Environmental Change (Schmidt, Kemfert, Höppe, 2010) and Environmental Impact Assessment Review (Schmidt, Kemfert, Höppe, 2009).
[2] 1 kt = 1.852 km/h

US$ (2005 values). Accordingly, the capital stock at risk $cs_j(y)$ from storm j in year y is determined as follows:

$$cs_j(y) =$$

$$\sum_{s=1}^{S}\left(residential\ units\ in\ counties\ beneath\ wind\ field_j(y)_s \times median\ home\ value(y)_s\right) \quad (2.1)$$

The index s represents the US states affected by the particular storm j. All figures are inflation-adjusted values in US$ (2005 values).

The statistical factor of residential unit encompasses houses, apartments, mobile homes, groups of rooms and individual rooms used for accommodation. Data on each county are available from the US Census (cf. Bureau of the Census, 1993, US Census, Census 2000 Summary File 3). No data are available for the average value of residential units. Information is used instead on the average (median) home value, which is available for each US state from the US Census (cf. US Census, Historical Census of Housing Tables, http://www.census.gov/hhes/www/housing/census/historic/values.html).[3] Both factors, i.e. the number of residential units and the median home value, are surveyed every 10 years by the US Census. Data for the intervening years have been generated by linear interpolation, while the figures for 2001–2005 were obtained by linear extrapolation.

Table 2.1: US states for whose counties the capital stock was estimated.

US state	
Alabama	New Hampshire
Arkansas	New Jersey
Connecticut	New York
Delaware	North Carolina
District of Columbia	Ohio
Florida	Pennsylvania
Georgia	Rhode Island
Indiana	South Carolina
Kentucky	Tennessee
Louisiana	Texas
Maine	Vermont
Maryland	Virginia
Massachusetts	West Virginia
Mississippi	

[3] The distribution of residential units and their values is a function of geography. The tendency for wealth to concentrate on coasts means that using the median home value for a state is going to skew the results to emphasise inland locations, where there is likely to be less wealth. Unfortunately, no data are available on the median home value at county level.

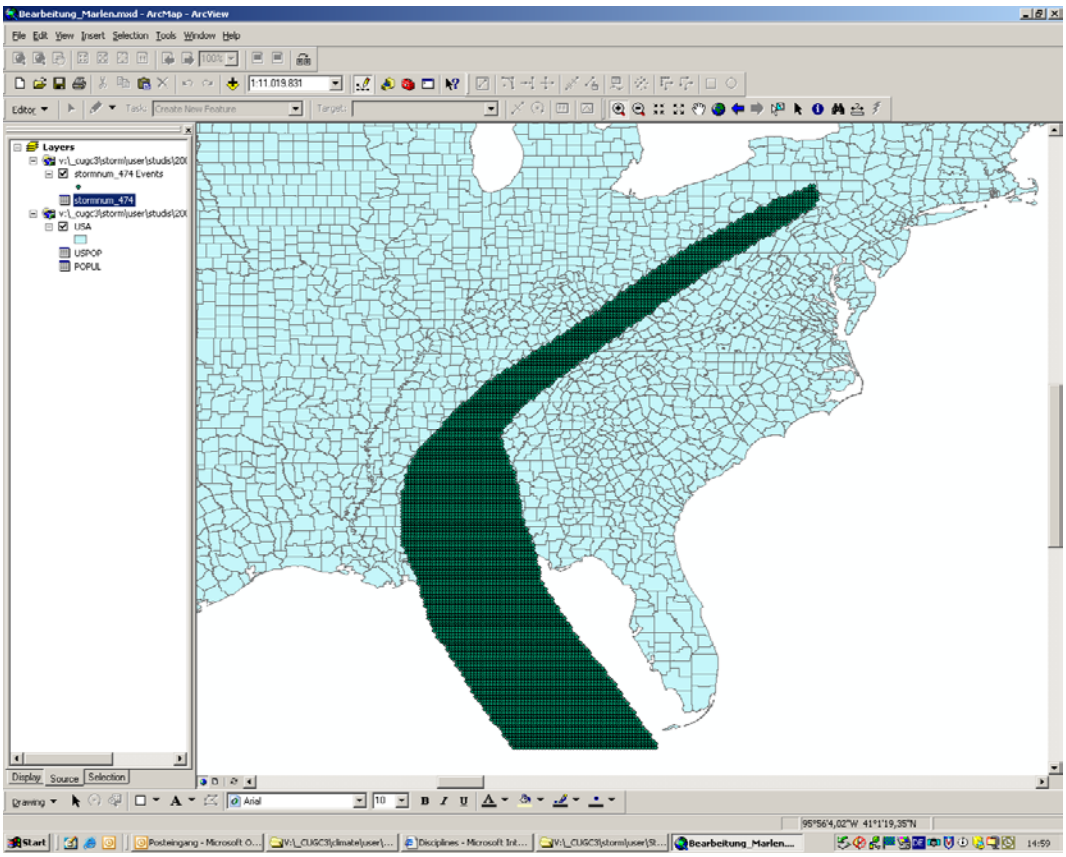

Figure 2.1: Region affected by Hurricane Frederic (1979). The wind field covers all US counties in which wind speeds >63 km/h were measured (data source: wind field is based on data from the Storm Track Dataset from the NOAA Coastal Services Center, http://maps.csc.noaa.gov/hurricanes/download.html; graphic: author).

One drawback encountered when using capital stock as a factor is that storm losses basically comprise building repair costs. While buildings may be completely destroyed in some cases, most losses involve repairing damaged buildings. The loss amount therefore depends more on the cost of materials and labour than on property prices. Capital stock is used because of the lack of data and to reduce complexity in the loss function.

A further drawback that should be mentioned is that the capital stock factor only incorporates the price and the number of residential units. In other words, assets within the units are not taken into account. Likewise, no allowance is made for infrastructure, or for industrial or office premises. In addition, median home value also includes the land value, which can account for a large portion of the sale value determined by the US Census. So the figures given here for capital stock can only be seen as an approximation of the actual capital stock in the affected regions. We therefore describe this proxy factor as a capital stock index.

Pielke Jr. et al. (2008) used an alternative method for estimating the capital stock at risk, by combining the population in the most seriously hit coastal counties and the national per capita capital stock. National per capita capital stock can be established from data obtained from the Bureau of Economic Analysis on national figures for fixed assets and durable consumer goods. However, using this national parameter means assuming an even distribution of wealth throughout the USA. Given the differences in the level of

wealth between the different US states, such an assumption is questionable. This point is illustrated, for example, by variations observed in the median home value between the different states (see Figure 2.3).

Despite these shortcomings, we believe the total residential unit value serves as a reasonable approximation of regional capital stock, particularly because data is in short supply and this approach makes allowance for regional differences in wealth.

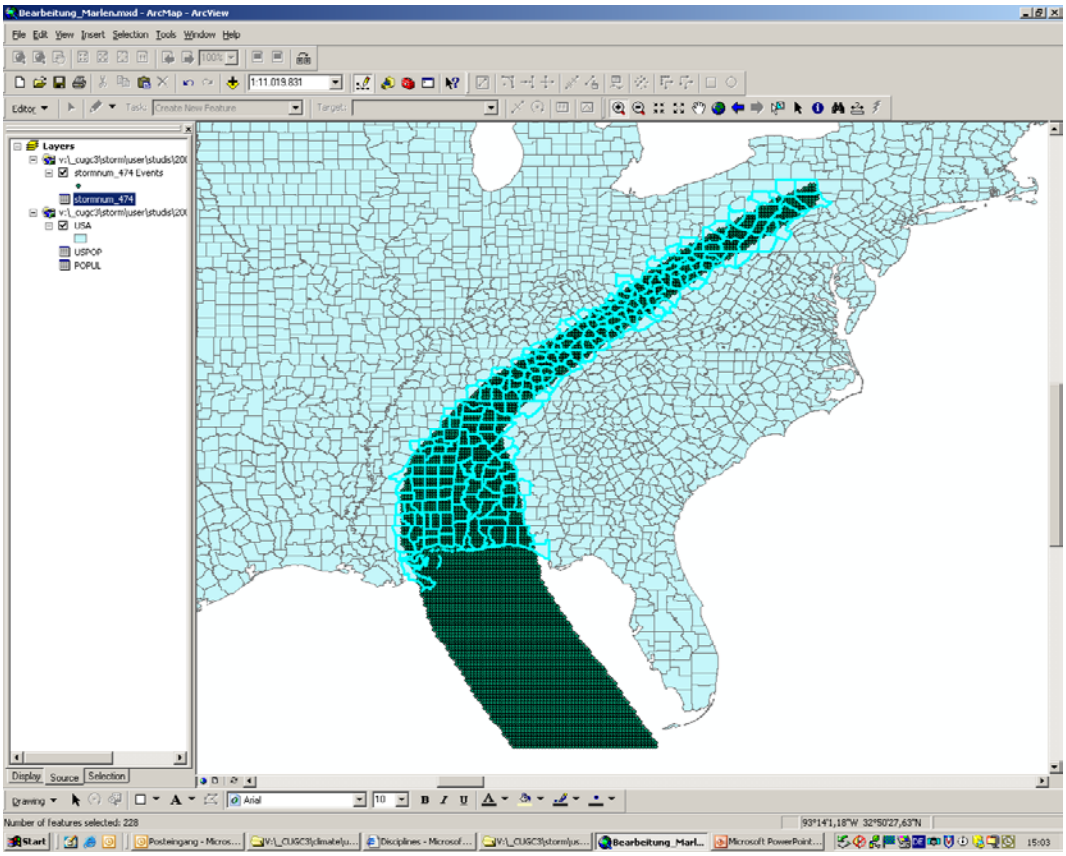

Figure 2.2: US counties affected by Hurricane Frederic (1979) (data source: wind field based on data from the Storm Track Dataset from the NOAA Coastal Services Center, http://maps.csc.noaa.gov/hurricanes/download.html; graphic: author).

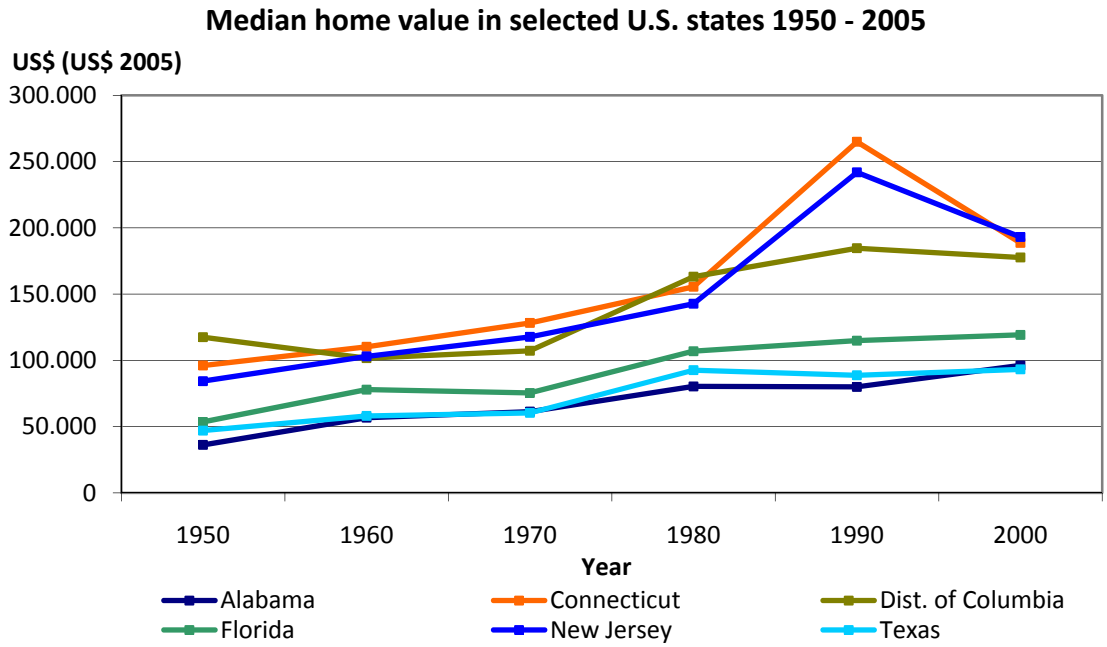

Figure 2.3: There are considerable differences in the levels of wealth between one US state and another. This is illustrated, for example by the average value of a detached house in US$ (2005 values) after adjustment for inflation (data source for the nominal average values: U.S. Census, http://www.census.gov/hhes/www/housing/census/historic/values.html, download 27.07.07; graphic: author).

2.2 Data on wind speed

The next factor, which is recorded for each storm in the database, is the intensity with which the storm impacts on the capital stock. For this we use the maximum wind speed recorded at landfall. The maximum wind speed is calculated as the highest one-minute average value recorded. The actual maximum wind speeds may therefore be higher. Furthermore, since they depend on the surface topography, they may vary away from the point where the measurements are made (cf. Pielke Jr. and Pielke Sr., 1997).

Over land areas, tropical cyclones generally reach peak intensity at landfall. After this point, the storm is cut off from its energy source and gradually weakens as it moves inland. For this reason, the storm impacts on the capital stock of different counties with varying intensity. As a rule, the capital stock in counties further inland is exposed to lower wind speed. For simplification purposes, this paper restricts itself to assuming the wind speed at landfall for all the counties affected. Such a simplification must be viewed in a critical light. Although regional wind speed data are available, there is no information on regional losses. This makes it impossible to break losses down by wind speed and is the reason for our assumption of a uniform wind speed. The wind speed at landfall data are taken from the Hurricane Track Tool of the National Oceanic and Atmospheric Administration (cf. NOAA Coastal Services Center, Historical Hurricane Tracks, http://hurricane.csc.noaa.gov/hurricanes/).

2.3 Data on economic loss

The third factor for each storm is the economic loss it caused. Natural catastrophe loss estimates are undertaken by a wide variety of institutes, such as the UN, national authorities, aid agencies such as the Red Cross, and of course, insurance companies. Each has its own method of evaluating loss and there is no standard procedure. Loss estimates therefore vary according to source and are not entirely comparable. A discussion of the different loss databases and the quality of loss data can be found in Dlugolecki (2007), Pielke Jr. et al. (2006) and Tschoegl et al. (2006). Downton and Pielke Jr. (2005) note that, for flood damage in the USA, the accuracy of loss estimates from different sources increases in proportion to the scale of the loss. In contrast, there is a wide variation in values for smaller flood events.

The reason for the deviations between different sources is basically that assessing losses from a natural catastrophe is a difficult and complex process. Pielke Jr. and Pielke Sr. (1997) offer a good illustration of the problems relating to losses from tropical cyclones. A wide range of aspects needs to be taken into account for the loss estimate. On the one hand, there are so-called direct losses that are immediately caused by the event. Examples of this category could include houses that have been damaged or destroyed by wind or flooding. Such direct effects can be estimated on the basis of payments by insurance companies, state aid, or from the reconstruction costs for public infrastructure. Then there are so-called indirect effects, which only occur days, weeks, or months after the event. One such effect, for example, could be a rise in insurance premiums. In addition, long-term effects may be experienced. Pielke Jr. and Pielke Sr. (1997) cite a drop in tax income in the region, in turn leading to a reduction in services financed by taxation, as one example of this kind of effect. It is generally extremely difficult to assess indirect and long-term effects, which is why most statistics do not include them.[4] As a result, loss statistics only provide a limited picture of the actual losses from natural catastrophes (see also Center for Health, 2005, Changnon et al., 2000, Hallegatte, 2008, Mills, 2005). But even with direct losses, it is difficult to make accurate estimates. Downton and Pielke Jr. (2005) compare the loss estimates for public infrastructure made immediately after an event with the reconstruction aid that was actually paid out in the end. For smaller events, there is a high error margin between loss estimates and actual costs, while in the case of moderate loss events, the estimates tend to be below the actual costs.

It should also be remembered that it is difficult, when assessing losses following a natural catastrophe, to allocate losses to their proper source (cf. Pielke Jr. and Pielke Sr. 1997). The effects of natural weather extremes are often merely the result of human errors. A natural phenomenon is often simply the trigger, while the causes can be found leading up to the event, for example a method of construction that is not updated to cope with the risk situation. Apart from allocating the loss, it is also difficult to quantify a loss that cannot be measured, or at least only to a limited degree in monetary terms. For example, what is the value of a missed lesson at school? Ethical questions also need to be addressed in this context. What value

[4] Examples illustrating the estimation of aggregate direct and indirect economic losses can be found in Hallegatte (2008) and Kemfert (2007).

should be put on the life of a victim? Furthermore, natural catastrophes not only cause losses, but can also produce benefits, such as the reconstruction work generated for the construction industry. Another benefit comes from protective measures that are adopted in the wake of an event, which help to reduce future losses.

We have already mentioned one of the topics of this paper, which is the comparability of losses over time. If no consideration is given to the fact that the increase in population and wealth in the regions exposed to natural hazards is the principal reason for the increase in losses, false conclusions may be drawn for the purpose of making political decisions (cf. Pielke Jr. and Pielke Sr., 1997).

It is clear that there are considerable difficulties involved in estimating the actual loss from a natural catastrophe. We therefore need to define what is meant by loss in this paper. For our purposes, economic loss is understood to be material asset losses sustained as an immediate consequence of a storm. Intangible losses and indirect consequences are not included. The loss thus encompasses damage to residential, industrial and office buildings, as well as to infrastructure. It also extends to losses to contents, and to movable property outside buildings, such as vehicles. Losses sustained as an indirect consequence are not generally included, nor are long-term effects. Again, particularly in the case of great natural catastrophes, there are often price increases due to a surge in demand for construction and repair services. This phenomenon is known as a “demand surge” and is normally included in the loss data. The justification for this is that the loss estimates are largely based on the cost of restoring items that have been destroyed. In this paper, we shall calculate the economic losses using data from Munich Re’s NatCatSERVICE® database.

Established in 1974, the NatCatSERVICE®is now one of the most comprehensive databases of global natural catastrophe losses in existence. Every year, some 800 events are entered in the database, which now contains over 25,000 entries, including all “great natural catastrophes” of the last 2000 years, and all loss events since 1980.[5] Direct material losses and the corresponding insured losses are recorded for each catastrophe. Loss estimates are based, according to availability, on well-documented official estimates, insurance claim payments, or comparable catastrophe events and other parameters. The data are obtained from over 200 different sources. They are observed over a period of time, documented, compared and subjected to plausibility checks. Individual loss data, estimates for the event as a whole, long-term experience and site visits are all used to produce well documented and clearly substantiated loss figures, which are then entered in the NatCatSERVICE® (cf. also Faust et al., 2006 and Munich Reinsurance Company, 2001, 2006). Information provided by the Property Claims Service (PCS) is key to NatCatSERVICE® estimates of US tropical cyclone losses.

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[5] A natural catastrophe is considered "great" if fatalities are in the thousands, the number of homeless in the hundreds of thousands, or if material losses are on an exceptional scale given the economic circumstances of the economy concerned (cf. Munich Reinsurance Company, 2007, 46).

The NatCatSERVICE® loss estimates also include losses at big industrial plants and offshore installations, such as large factories, airports and oilrigs. However, the capital stock figures used in this paper relate only to the total value of the residential units in the counties affected and exclude large industrial plants and offshore installations. Therefore, to the extent possible, losses at large plants and offshore installations have been deducted from the estimated loss. The NatCatSERVICE® does, in fact, provide loss information for large industrial plants and offshore installations, but not for smaller factories and installations. These losses have not therefore been deducted from the estimated overall loss, even though our capital stock index does not take these facilities into account either.

For the period 1950 to 2005, the NatCatSERVICE® lists 113 North Atlantic storms that made landfall in the USA. Storms that made landfall several times, i.e. where the storm returned to the open sea after initial landfall and subsequently made two or even three landfalls, have been divided into their constituent events. This reflects the fact that the storm condition changes as it draws fresh energy from the warm sea surface. Consequently, the data set comprises 131 storm events in total. In the case of storms with multiple landfall, the overall loss was divided among the individual occurrences. The breakdown was carried out by determining the regions affected by each landfall. The proportion of overall losses for each region affected was based on the aggregate and regional losses reported by the Property Claims Service (PCS) (cf. PCS, https://www4.iso.com/pcs). The overall loss figures from the NatCatSERVICE® were split in the same proportion. The NatCatSERVICE® itself has only aggregate storm loss details. We were not able to apportion the figures in every instance, for example in cases where storms made landfall twice in the same state, or if the loss was below the threshold at which storms are recorded in PCS Catastrophe History, since the PCS only records storm events above a particular loss amount.

2.4 Quality of data on economic losses

As shown in Figure 1.2, one factor behind the loss trends may be the technique used to record and evaluate the losses (the data reporting factor). In the previous section, we already discussed the difficulties associated with evaluating losses from a natural catastrophe. But even where a method is systematically applied to assess the losses, as in the case of the NatCatSERVICE®, some of the data may be skewed. One reason for this may be the increasing number of ways of obtaining information on catastrophes thanks to the steady expansion in global networking. Another is that there is more reporting on particular natural catastrophes due to increased public perception. For example, an increased number of reports on weather-related natural catastrophes was observed in the media that coincided with the development of the debate on anthropogenic climate change (cf. Faust et al., 2006). But information on natural catastrophes can also be deliberately over- or underestimated. For example, we note that the number of natural catastrophes and the loss figures recorded in the NatCatSERVICE® for the People's Republic of China have increased significantly since the country opened up to the outside world in the early 1980s. On the one hand, this may be an indication that the NatCatSERVICE® has had greater access to information on natural catastrophes in China since the country abandoned its policy of self-imposed isolation. In addition, we could assume that, in the past, the impact of natural catastrophes was deliberately played down by the authorities. Official reporting of exaggerated or understated information may be prompted by the desire to obtain more international aid, on the one hand, or to play down a catastrophe so as not to give

any reason for outside intervention. For the operators of loss databases, it is therefore important to obtain information from as many sources as possible in order to obtain reliable loss estimates.

The NatCatSERVICE® loss estimates used in this paper were first subjected to a quality evaluation[6], allowing us to ascertain for which period reliable loss data are available. A method was first devised for the quality evaluation, which was then applied to the NatCatSERVICE® database. Each dataset (corresponding to one natural catastrophe event) was given a quality rating between one and six. The mark one represents the highest data quality, while the mark six is the lowest. Table 2.2 explains the different quality levels for marks one to six. The rating is based on the underlying sources and on how closely the loss description corresponds with the loss amount. The decision tree shown in Figure 2.4 was developed to ensure a standardised approach to the rating process. First-class sources are believed to provide information that is highly reliable. Such sources include insurance companies or insurance bodies, scientific institutions, international organisations (such as the UN, IFRC, or WHO), or specific news agencies (such as Reuters and dpa). Reports from selected newspapers and insurance brokers are defined as information from second-class sources. Information from third-class sources is derived from historical records and from selected Internet sources (cf. Faust et al., 2006).

The evaluation of the quality of the loss data shows that loss information on the so-called "great natural catastrophes" since the 1950s is very reliable (with marks 1 and 2 in each case). Information on smaller and medium events is assessed as reliable for most countries from the 1980s on. Reliable information is already available for the USA from the 1950s (see Figure 2.5). Based on this result, the present paper only includes data on losses from tropical cyclones in the USA from 1950. Miller et al. (2008) draw the same conclusion on data quality for storm losses in the USA.

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[6] A quality assessment for all of the NatCatSERVICE® database was carried out as part of a subproject for this dissertation.

Table 2.2: Overview of the quality levels according to which the NatCatSERVICE® datasets are allocated (source: Faust et al., 2006; own representation).

Quality level	Description
Quality level 1	Loss assessment with very good reporting
Quality level 2	Loss assessment with good reporting
Quality level 3	Loss assessment with satisfactory medium reporting
Quality level 4	Loss assessment with sufficient, brief reporting (loss amount without clear plausibility)
Quality level 5	Loss assessment with faulty, poor reporting (loss amount without plausibility). Dataset (loss assessment) cannot be used for analysis
Quality level 6	Loss assessment with inadequate or missing reporting. Dataset (loss assessment) cannot be used for analysis

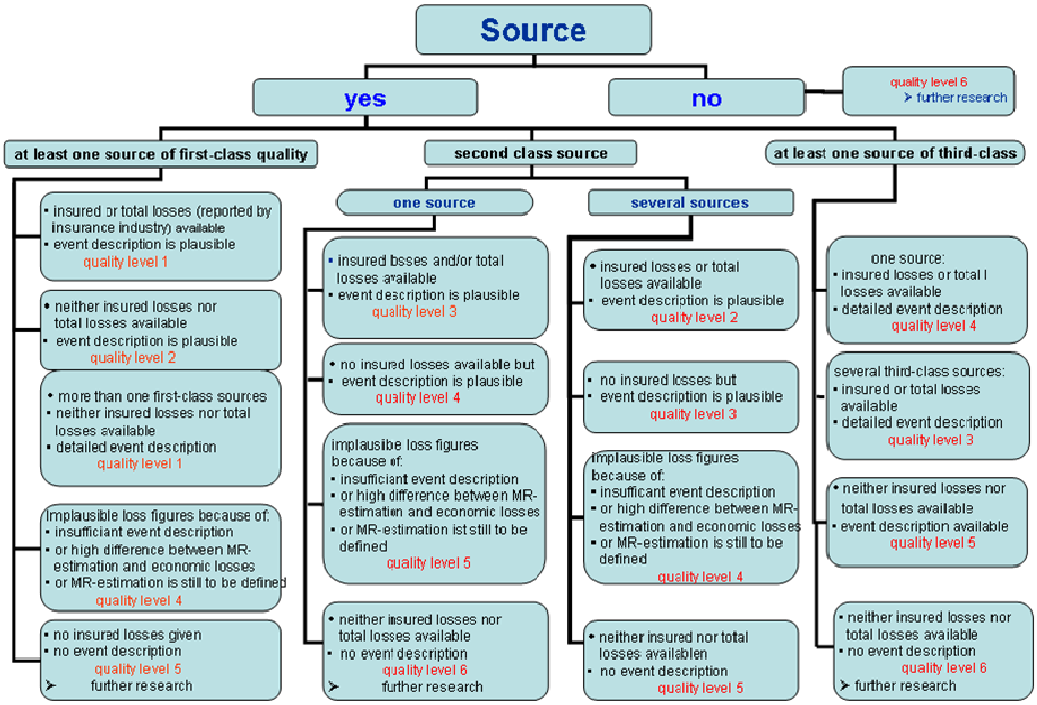

Figure 2.4: Decision tree for allocating datasets to quality levels (source: Faust et al., 2006).

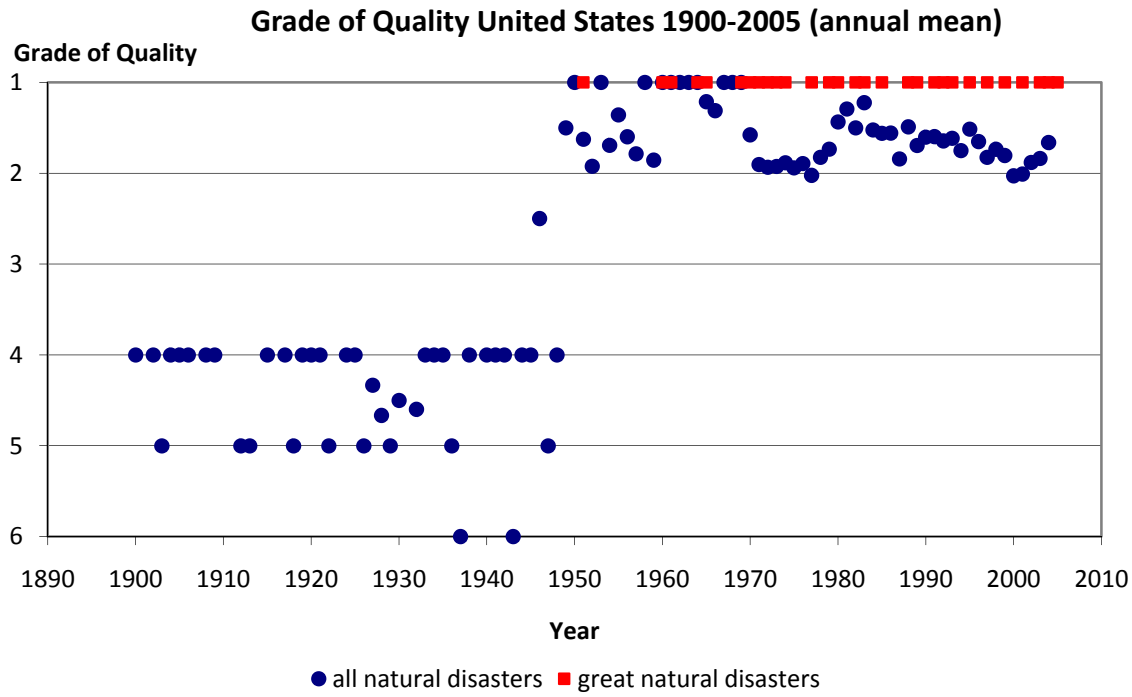

Figure 2.5: Quality of the datasets on natural catastrophes in the USA (source: Faust et al., 2006).

3 Methods

3.1 Selection of methods

Various methods are used in this doctoral thesis. This chapter begins by explaining why a particular method was selected for a particular problem. Next, the different procedures are presented in detail. The chapters describing the individual studies will again look briefly at the methods used.

The thesis is divided into two parts. The first part, which is devoted to two of the three studies, will examine what portion of the overall trend in losses is made up of to socio-economic and climate-related losses. The second part will look at different scenarios for storm losses in the future, taking into account both socio-economic and climate-related trends.

Two different methods can be used to investigate the portion of the overall trend that can be accounted for by socio-economic and climate-related losses. This can either be done using a time series analysis, or by using other methods, such as regression analysis, that determine the dependency between the loss and the socio-economic and climate-related factors.

The first study uses a time series analysis. It examines empirical storm losses for trends that could have been caused by climate change. The first step is to adjust the loss data for any socio-economic influences they may contain. Once increases in population and material assets no longer influence the loss trend, any remaining trend must stem from factors for which the losses have not been adjusted. This procedure is similar to that used to adjust for inflation. After adjustment for inflation, for example, any persisting trend in the price trend for an item must be caused by something other than inflation. In the case of the first study, a remaining trend can be traced back to climate change, but could equally be attributed to other factors. It is not possible, therefore, to clearly determine the role played by climate change. A further drawback with this method is that the level of the remaining trend is highly responsive to the start and end points that are selected for the trend analysis. In view of the high variability of the annual losses, this has a significant influence on the results in our case. For this reason, the first study takes the average of several annual losses instead of a single annual loss for the start and end points of the trend analysis. Despite the inherent limitations, this is the procedure adopted for the first study. The approach of firstly adjusting losses for socio-economic effects, and then subjecting them to a trend analysis, was first used in the study by Pielke Jr. and Landsea (1998). This is currently the central approach in the literature for investigating empirical loss data for a possible climate signal (cf. Crompton and McAneney, 2008, Miller et al., 2008, Pielke Jr. et al., 2003, Pielke Jr. et al., 2008, Raghavan, 2003).

The second study looks at the extent to which the storm loss depends on the capital stock at risk and the storm intensity. Specifically, it estimates the elasticity of the storm loss to a change in capital stock or a change in storm intensity. The estimate is carried out with an optimisation method for non-linear relationships (in this instance the Levenberg-Marquardt algorithm). A conclusion is drawn about the share that both factors have in the overall trend by analysing the respective trends for the two factors. Unlike the procedure used in the first study, this allows us to make a direct inference about the influence of climate

change. In addition, the socio-economic influences are not eliminated, but are explicitly incorporated into the procedure. If the two approaches are compared, this latter seems better suited to explain what portion of the overall loss trend stems from socio-economic and climate-related developments. A drawback with this approach is that here, once again, the results are influenced by the underlying time series segment for the historic development of capital stock or of storm intensity. As in the first study, the analysis here concentrates on the period 1950–2005. If the study were extended to include the year 2008, the current US property market crisis would influence the capital stock share. While the trend in storm intensity has not shown a critical drop since 2005, as the capital stock, it is still basically very volatile. For that reason, we fall back on mean values covering several years here as well. A further drawback relates to the optimisation procedure selected. Start values need to be specified for the optimisation. Accordingly, there is no absolute guarantee that there is not a different parameter combination to the one estimated that reproduces the relationship more precisely. However, this uncertainty can be reduced by repeating the optimisation with different start values. For non-linear parameters, multiple regression analysis, where the non-linear relationships are first converted to a linear one, offers an alternative to the optimisation method used. A decision was taken to use the Levenberg-Marquardt algorithm, since it leads to statistically more significant results in our case.

The time series analysis of loss data that have been adjusted for the influence of socio-economic factors, and also the analysis of the dependency structure between loss and influencing factors are both suited for analysing the role of the individual factors in the overall loss trend. Ultimately, any approach only permits an approximate quantification of the share that climate-related and socio-economic developments have in the overall loss trend. The thesis therefore deliberately presents different ways of analysing the influence of climate change and socio-economic effects.

The third study simulates the future average annual loss, assuming a further increase in capital stock and an intensification of the storms as a result of global warming. A stochastic model, whose components are the number of storms and the individual loss per storm, is used for the simulation of the annual loss. An average annual loss is determined from 10,000 annual losses simulated using a Monte Carlo simulation. Using the model, we can simulate both the effects of a change in storm frequency, and also a change in the distribution of the individual storm losses. The procedure chosen is a standard one in the insurance industry (cf. Katz, 2002a). It is used when the amount of the loss from several loss occurrences needs to be estimated, and both the number and the individual loss are unsure. An alternative procedure would be to extrapolate the observed storm loss trend to the future (as did Stern et al., 2006). However, the trend determined in the first study cannot be broken down into its separate components of natural climate variability and anthropogenic climate change. This makes it difficult to find a trend function that allows a reliable forecast to be made. It would need to simulate the different-length cycles in natural climate variability and the linear or exponential increase resulting from global warming. As a result, a trend extrapolation is therefore only applicable for short-term loss forecasts at best.

The preparation of data is extremely labour-intensive for all three studies. The information on the capital stock at risk is required for each separate storm event. It is therefore not automatically possible to conduct the analyses with a different or an expanded database. The database for storms from the years 1950–2005

is used as the basis for analysis throughout this thesis. If this database were expanded, for example to include data that is now available on the storms in the years 2006–2008, it would necessitate the recalculation of the capital stock for every storm in the database.[7] As explained in the chapter on data on the capital stock at risk, the first step in this process is to determine the region affected by each storm by using the geographic distribution of the measured wind speeds (wind field). This data is then combined with a map of the capital stocks in the different US counties. The GIS technique admittedly makes the work involved much easier. However, since the procedure described has to be carried out for each storm in the database both for the year of occurrence and also for the base year, it is still a fairly time-consuming process.

The following chapters will present in detail the methods used in the three studies.

3.2 Method used for the trend analysis of adjusted loss data[8]

The main object of the first study is to test the hypothesis that climate-change factors are to some extent responsible for the increase in losses. To identify trends that may be due to climate change, the loss data have to be adjusted to exclude socio-economic impacts. Normally, loss data are inflation-adjusted only for comparison purposes. However, population trends and the quantity and value of assets in the exposed areas account for much greater changes than an appreciation in the value of money.

Nordhaus (2006) demonstrates one way of adjusting the figures to exclude the effects of increased wealth. He adjusts storm losses in relation to gross domestic product (GDP) in the year of occurrence. However, GDP, which reflects the value of goods and services that are produced annually, is only suitable to a limited extent as a means of evaluating natural catastrophe losses (cf. Steiniger et al., 2005). The stock of material assets accumulated over decades is more significant in determining the amount of such losses than the goods and services the economy produces in the course of the year. However, since no data are available for many parts of the world on the quantity of assets, GDP has to be used. If possible, regional GDP figures should be used, since the impact of natural catastrophes is generally confined to a particular region.

Pielke Jr. et al. (2008) adjust losses to discount the effects of inflation, population growth and increased wealth. Population changes are measured using the ratio of current population to population in the year of the storm event. Changes in wealth are ascertained by applying the ratio of current per capita wealth to per capita wealth in the year of the storm. The adjusted loss is established by multiplying the inflation-

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[7] In preparing this thesis, it seemed appropriate to update the analyses in the publications by incorporating the storms from the years 2006-2008, but I decided against this because of the effort it would involve. A further reason is that it would have restricted comparability with the key papers by Pielke Jr. et al. (2008) and Nordhaus (2006), since both papers only include loss data up to, and including, 2005.

[8] This section is based on a publication in Environmental Impact Assessment Review (Schmidt, Kemfert, Höppe, 2009).

adjusted loss by population change and per capita change in wealth. This so-called "Normalized Hurricane Damages" approach was first used by Pielke Jr. and Landsea (1998) for the USA. It was subsequently adopted by Miller et al. (2008) and others and adapted to other regions and natural catastrophe types.

Collins and Lowe (2001) take Pielke Jr. and Landsea's (1998) approach a stage further by substituting the change in population with the change in the number of residential units. The losses are then adjusted according to the change in wealth per residential unit. There are also a number of other studies that have used housing values to adjust losses. Crompton and McAneney (2008), for instance, used the number and mean value of dwelling units to adjust losses due to weather disasters in Australia.

The first study in this thesis eliminates the socio-economic components from the losses on the basis of changes in regional capital stock, which is the value of the material assets in the region expressed in US$. Since storm losses are essentially a function of storm intensity and material assets located in the area, it is believed that it is more appropriate to apply an adjustment based on capital stock than on the general evolution in wealth measured by GDP, or change in population and per capita wealth. The adjustment is based on the change in the capital stock index of all US counties in which a specific wind speed was exceeded (>63 km/h). The rationale is that wind speeds above this threshold cause substantial losses. The method is founded on the papers by Pielke Jr. and Landsea (1998), Collins and Lowe (2001) and Pielke Jr. et al. (2008), referred to above.

The adjustment per storm j can be expressed as:

$$x_k(y) = x_j(y) \times \frac{cs_j(2005)}{cs_j(y)} \tag{3.1}$$

$x_k(y)$ storm j losses adjusted to socio-economic conditions in 2005

$x_j(y)$ inflation-adjusted losses from storm j with the socio-economic conditions of year of occurrence y

$cs_j(2005)$ index for the value of all material assets in 2005 in the US counties affected by storm j

$cs_j(y)$ index for the inflation-adjusted value of all material assets in occurrence year y in the US counties affected by storm j

Amounts are in inflation-adjusted US$ (2005 values).

Adjusted losses $x_k(y)$ from storm j are ascertained by multiplying the actual loss $x_j(y)$ by a factor expressing the ratio of 2005 capital stock $cs_j(2005)$ to actual capital stock in the year of occurrence $cs_j(y)$. The adjusted losses thus obtained provide better comparability as they are no longer affected by the socio-economic conditions prevailing in the different years.

Any residual trend in annual adjusted losses $D(y)$ is determined using a linear regression (ordinary least squares fit):

$$\ln\big(D(y)\big) = \alpha + \beta \times time_y + \varepsilon_y \tag{3.2}$$

$D(y)$ is expressed by the factor *time* in year y, α being a constant and ε_y the error term. If β is positive, this indicates an upward trend over time. As well as performing an analysis to establish a possible trend, we also calculate the average growth rate in annual losses w, which can be found using the geometric mean:

$$w = \big(D_m(y) \div D_1(y)\big)^{\frac{1}{(m-1)}} - 1 \tag{3.3}$$

Value m being the number of years analysed in the time series. Average growth rate is thus calculated in accordance with the loss in the first and last years of the time series.

3.3 Method used for determining loss sensitivity to climate change and socio-economic effects[9]

The basic premise is that a storm loss can be expressed as a function of socio-economic and climate-related factors. Specifically, it is assumed that the economic loss can be calculated from the value of the material assets (capital stock) in the region affected by the storm and the intensity with which the storm impacts those assets. The capital stock variable represents the socio-economic components. The wind speed at landfall variable represents the climate-induced component (intensity).[10]

Population is not included since it has only an indirect effect on economic losses caused by storm. Generally, the higher the population, the greater the quantity of material assets and thus, indirectly, the higher the losses. This factor is reflected in the loss function in the form of capital stock. On the other hand, loss of life, labour shortages, lower earnings and other factors directly linked to population, are not normally included in economic losses (refer to the chapter on data and data sources).

In fact, a number of other factors are involved, such as vulnerability of assets to storm damage, surface topography, wind profile and effectiveness of disaster-prevention measures. However, in the absence of

[9] This section is based on a publication in Regional Environmental Change (Schmidt, Kemfert, Höppe, 2010).
[10] There are indications that the intensity of tropical cyclones is affected by climate change. The destructive force of tropical cyclones has been increasing globally since the mid-1970s. This correlates very closely with the sea surface temperature (SST) (cf. Emanuel, 2005a, IPCC, 2007a, and Webster et al., 2005). According to Barnett et al. (2005) there is also a correlation between SST and anthropogenic greenhouse gas emissions. However, the SST is not the only factor that influences intensity. It is possible that other factors are even more important, e.g. wind shear (cf. Bengtsson et al., 2007, Chan, 2006, Emanuel et al., 2008, Knutson and Tuleya, 2004, Vecchi et al., 2008). Climate change has an impact on various parameters like ocean temperature, atmosphere, circulation, and water vapour, and hence influences tropical storms. The processes involved are complex and not yet completely understood (cf. Wang and Lee, 2008).

sufficient data to quantify them, the simplified view is taken that only total asset value and wind speed are relevant (see also Sachs, 2007).

This fundamental premise can be expressed by the following mathematical formula:

$$x_j(y) = f\left(cs_j(y), ws_j\right) \tag{3.4}$$

with $x_j(y)$ being the inflation-adjusted loss from storm j in year y, $cs_j(y)$ being the capital stock index affected by storm j and ws_j being the wind speed of the storm.

The normal loss function in which storm loss is a power function of wind speed ($x_j = \alpha \times ws_j{}^{el}$; [cf. Howard et al., 1972]) is thus extended to include a capital stock index. Parameter α is divided into β and variable $cs_j(y)$ for capital stock index. Thus, the loss function to be estimated is:

$$x_j(y) = \beta \times cs_j(y)^{el_1} \times ws_j{}^{el_2} \tag{3.5}$$

Parameters el_1 and el_2 indicate how much the loss changes if the capital stock index or wind speed change by one unit (elasticity). The Levenberg-Marquardt algorithm is used to estimate this non-linear loss function. As a following step, one needs to consider the extent of climate-related and socio-economic changes in the past in order to determine the historical impact of climate-related changes and socio-economic effects.

3.4 Method used for the simulation of economic losses from cyclones[11]

A stochastic model that determines an average annual loss from a large number of generated annual losses is used for the simulations in the third study. The model consists of two components. The first determines the number of loss events, which, in our case, is the number of storms in the space of one year. The second component determines the individual loss amount for each of the different loss events, which here represents the loss per storm. The annual loss is obtained from the number of events and the individual loss per event, as the sum of two independent random processes. The high variability in the annual storm loss observed in reality is thus simulated using the variation in the annual number of storms and the variation in the loss caused in each case. The method described in the model is normally used in insurance mathematics to determine the expected loss amount from several loss events, where the number of loss events and the loss amount in each case are uncertain. The model described below is similar to a model presented by Katz (2002a) for simulating tropical storm losses. Rootzén and Tajvidi (1997) also applied a comparable method for extratropical storm losses.

[11] This section is based on a submission to Global Environmental Change (Schmidt, Kemfert, Faust, 2009).

Model description

Frequency

The number of cyclones is expressed by the random variable *N(t)*, with a random number of storms within the time interval [0;*t*]. It is assumed that the random variable *N(t)*, is Poisson distributed (cf. also Hallegatte, 2007a, Katz, 2002a, Nordhaus, 2006,). The probability that precisely *k* storms occur within the time interval is therefore:

$$\Pr\{N(t) = k\} = \frac{\mu^k}{k!} exp^{-\mu} \tag{3.6}$$

The parameter μ corresponds here to the expected value for the number of storms within the time interval.

Loss per storm

The random variable $X_k > 0$ represents the loss that is caused by the *k*-th storm within the time interval. In reality, it can be observed that many storm events occur with small losses, while just a small number of storm events causes major losses. This implies that the frequency distribution of the losses follows a distribution similar to lognormal distribution. This is also assumed for the distribution *F* of the random variable X_k. The distribution of the losses is expressed as follows via the density *f* of the lognormal distribution:

$$f(x) = \frac{1}{\sigma x\sqrt{2\pi}} \times \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \tag{3.7}$$

It is further assumed that the different X_k variables are independent of one another, and that the sampling of X_k is independent from the sampling of *N(t)*.

Annual loss

The loss from all storms within the time interval [0;*t*] is the total of losses for the individual storm events. For a time interval of one year, this annual loss is *D(t)*:

$$D(t) = X_1 + X_2 + \cdots + X_{N(t)}; N(t) \geq 1; \text{otherwise } D(t) = 0 \tag{3.8}$$

Model parameters

Assuming that a time series is available for the annual number of observed storms, the parameter μ required for the random process of the frequency can be calculated from $\{n_y, y=1, 2,..., m\}$. In this instance, n_y stands for the number of storms in the year *y* within a time series of *m* years. The estimate for parameter μ corresponds to the average number of storms per year within the time series.

$$\hat{\mu} = \frac{n}{m}; \text{where } n = \sum_{y=1}^{m} n_y \tag{3.9}$$

It is furthermore assumed that a database of observed storms in the form $\{x_k(y), k = 1, 2,..., n_y; y = 1, 2,..., m\}$ is available to express the distribution of losses per storm. $x_k(y)$ denotes the loss from the k-th storm in the year y. The mean, the standard deviation, and the minimum and maximum for the distribution of $x_k(y)$ are used to express the distribution F for the random variable X_k.

Model estimate

Use of adjusted loss data

The database of observed storms from the Munich Reinsurance NatCatSERVICE® is again used to estimate the model parameters. We adjusted the losses from the 131 different storm events to the socio-economic conditions in 2005. This eliminates the influence on losses from inflation, as well as from changes in population and wealth over time. The loss data are therefore in US$ prices for 2005 and at the level of wealth in 2005. To put it a different way, the losses are given as if all 131 storms had occurred in the year 2005. The loss $x_k(y)$ required for the parameter estimate is obtained by adjusting the inflation-adjusted loss $x_j(y)$ caused by storm j in the year y. For this, the inflation-adjusted loss $x_j(y)$ is multiplied by the ratio between the capital stock in the year 2005 in the region affected by storm j, expressed as $cs_j(2005)$, and the inflation-adjusted capital stock in the same region in the year y, expressed as $cs_j(y)$. The capital stock encompasses the value of all material assets in the region affected.

$$x_k(y) = x_j(y) \times \frac{cs_j(2005)}{cs_j(y)} \tag{3.1}$$

Following the adjustment, we have an adjusted loss $x_k(y)$ for each loss $x_j(y)$ at the level of wealth in the year 2005.[12]

Using the model, the average annual loss is estimated for a baseline scenario. This is done with the help of a Monte Carlo simulation based on the empirical distributions for storm frequency and individual storm loss. To simulate the average annual loss in the future, these distributions are then shifted to allow for the anticipated effects from climate change and growth in capital stock. An average annual loss is then determined once again using Monte Carlo simulations.

[12] See also the description of the method used for the trend analysis of adjusted losses.

4 A trend analysis based on data from a new approach to adjusting storm losses[13]

4.1 Introduction

The number of tropical cyclones that make landfall on the US Gulf and Atlantic coasts has increased distinctly in the investigation period 1950–2005, as shown by Figure 4.1. Cyclones are also causing greater economic losses in the form of loss or damage to material assets (see Figure 4.2). The principal causes are socio-economic developments, primarily, population growth, greater wealth and increased settlement of areas exposed to natural hazards, as mentioned in chapter 1. Other causes are changes in vulnerability to natural extremes and concentrations of people and material assets in conurbations. The trends observed may also be affected by natural and anthropogenic climate change (see Figure 1.2). As mentioned before the term "climate change" is used as defined by the IPCC in its Fourth Assessment Report, i.e. "Climate change refers to any change in climate over time, whether due to natural variability or as a result of human activity" (IPCC, 2007b, 871). The study here does not see itself in a position to make quantitative statements about the separate effects of natural climate variability and human activity. According to Höppe and Pielke Jr. (2006), this question is unlikely to be settled unequivocally in the near future. Nevertheless, the impact that climate change as a whole (due to both natural and anthropogenic forcings) has on loss trends is still worth looking at in more detail. The IPCC states that humans have more likely than not contributed to a trend in intense tropical cyclone activity since the 1970s. Any increase in losses could, more likely than not, be partly related to anthropogenic climate change.

The aim in this study is to exclude socio-economic impacts from the losses, thus enabling one to identify potential trends that may be due to climatic changes. The losses for the period 1950–2005 are adjusted to the socio-economic level of 2005 to eliminate the effect of socio-economic developments. The adjusted losses are then subjected to a trend analysis. Any remaining trend would not be attributable to socio-economic developments. Höppe and Pielke Jr. (2006) called for an agreed and peer-reviewed method for loss normalisation. This chapter adds an approach to the discussion of appropriate methods.

Miller et al. (2008) are conducting a similar analysis of worldwide annual losses for a number of weather-related natural catastrophes. To obtain comparable loss data, they adjust their losses with reference to trends in per capita wealth, inflation and population. A trend analysis of the adjusted loss data shows an annual increase of 2%, a remaining, positive trend which cannot be accounted for by global socio-economic developments. However, the trend is statistically significant only for the period 1970–2005 and is heavily influenced by the extreme hurricane seasons in 2004 and 2005.

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[13] This chapter is based on a publication in Environmental Impact Assessment Review (Schmidt, Kemfert, Höppe, 2009).

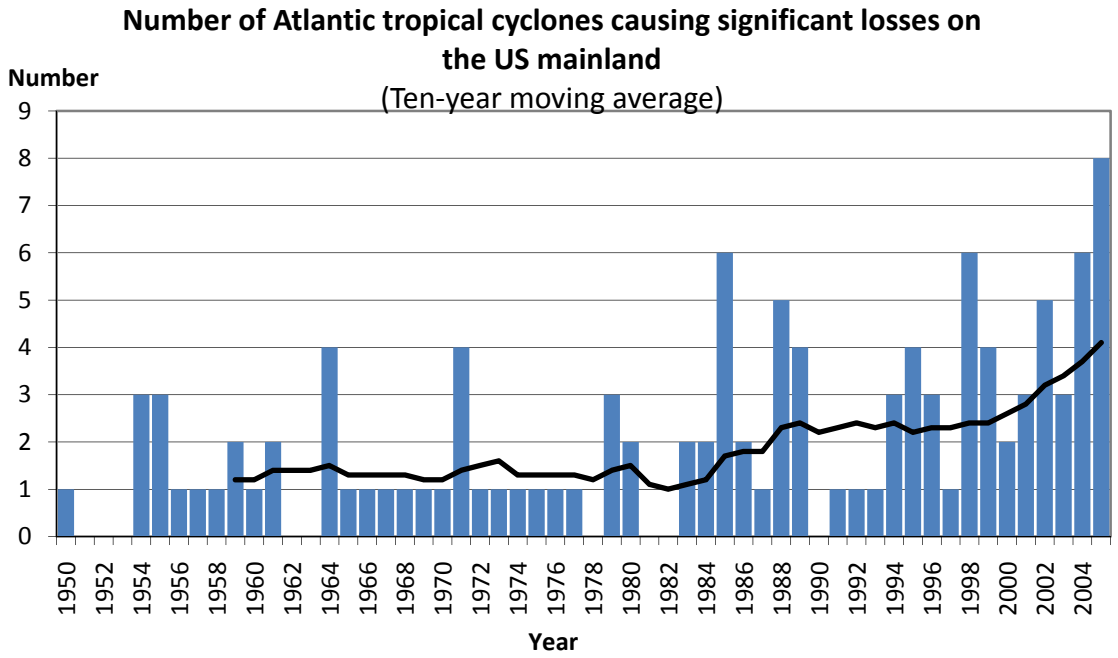

Figure 4.1: Annual frequencies of tropical cyclones that have caused significant losses on the US mainland (data source: Munich Re, NatCatSERVICE®, 2007; chart: author).

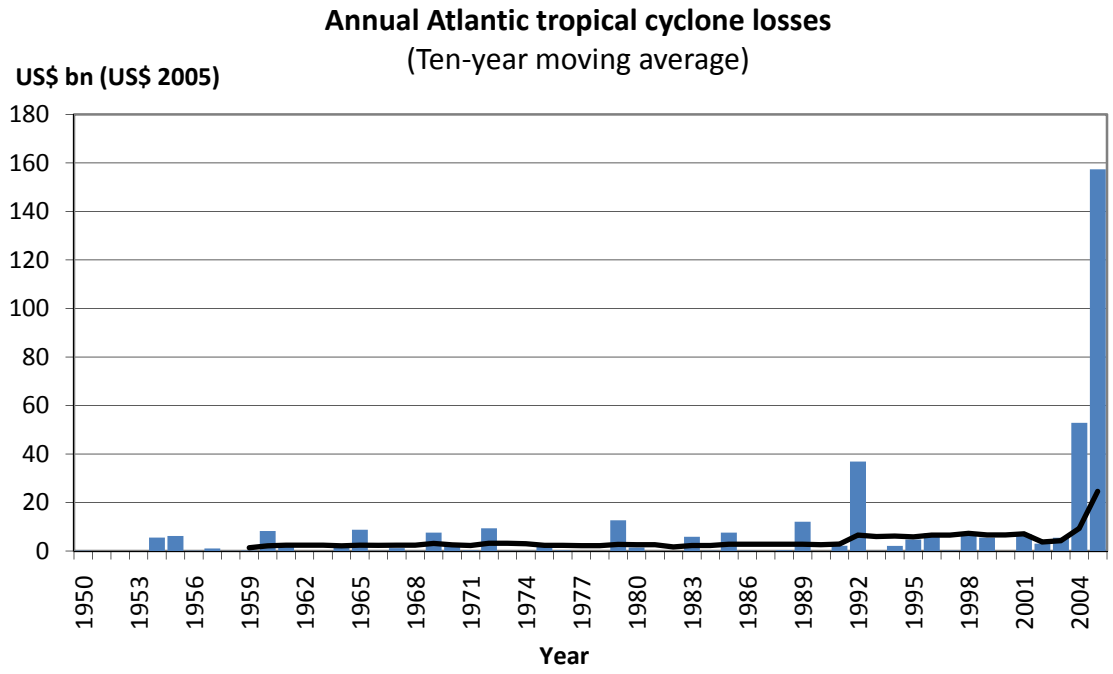

Figure 4.2: Annual inflation-adjusted losses caused by Atlantic tropical cyclones that made landfall on the US mainland in billion US$ (2005 values) (data source: Munich Re, NatCatSERVICE®, 2007; chart: author).

4.2 Method

The main object of the study is to test the hypothesis that climate-change factors are to some extent responsible for the increase in losses. To identify trends that may be due to climate change, the loss data have to be adjusted to exclude socio-economic impacts. Normally, loss data are inflation-adjusted only for comparison purposes. However, population trends and the quantity and value of assets in the exposed areas account for much greater changes than an appreciation in the value of money.

The study presented in this chapter eliminates the socio-economic components from the losses on the basis of changes in regional capital stock, which is the value of the material assets in the region expressed in US$. Since storm losses are essentially a function of storm intensity and material assets located in the area, it is believed that it is more appropriate to apply an adjustment based on capital stock than on the general evolution in wealth measured by GDP, as in Nordhaus (2006), or change in population and per capita wealth, as in Pielke Jr. et al. (2008). The adjustment is based on the change in the capital stock index of all US counties in which a specific wind speed was exceeded (>63 km/h). The rationale is that wind speeds above this threshold cause substantial losses.

As mentioned earlier the adjustment per storm *j* can be described as:

$$x_k(y) = x_j(y) \times \frac{cs_j(2005)}{cs_j(y)} \tag{3.1}$$

$x_k(y)$ storm *j* losses adjusted to socio-economic conditions in 2005

$x_j(y)$ inflation-adjusted losses from storm *j* with the socio-economic conditions of year of occurrence *y*

$cs_j(2005)$ index for the value of all material assets in 2005 in the US counties affected by storm *j*

$cs_j(y)$ index for the inflation-adjusted value of all material assets in occurrence year *y* in the US counties affected by storm *j*

Amounts are in inflation-adjusted US$ (2005 values).

Adjusted losses $x_k(y)$ from storm *j* are ascertained by multiplying the actual loss $x_j(y)$ by a factor expressing the ratio of 2005 capital stock $cs_j(2005)$ to actual capital stock in the year of occurrence $cs_j(y)$. The adjusted losses thus obtained provide better comparability as they are no longer affected by the socio-economic conditions prevailing in the different years.

4.3 Data

To convert storm losses occurring in different years to a comparable socio-economic level, information is required on the region affected, the capital stock located there and the loss caused.

The region affected by a storm comprises all the counties in which the storm caused substantial losses. This can be ascertained using the relevant wind field, which defines the area extent of the storm. It is the area in which a specific wind speed has been exceeded. In our case, the wind field includes all counties in which the storm was still classified as a "tropical storm", i.e., where wind speeds were at least 63 km/h. Considerable losses occur if this limit is exceeded. The wind fields are calculated using the Storm Track Dataset provided by the National Oceanic and Atmospheric Administration (NOAA Coastal Services Center, http://maps.csc.noaa.gov/hurricanes/download.html). The capital stock in the relevant counties is calculated for year 2005 as well as for the year of occurrence. An introduction into how to ascertain the capital stock in the relevant counties is given in chapter 2.1.

As well as calculating the capital stock in the counties affected, it is also necessary to ascertain the economic losses caused by a storm. For our purposes, economic losses are understood to be material asset losses sustained as an immediate consequence of a storm. Intangible losses and indirect consequences are not included. The loss accordingly comprises damage to residential, industrial and office buildings and to infrastructure as well as losses to contents and to moveable property outside buildings, e.g. vehicles. Losses sustained as an indirect consequence, on the other hand, are not included. On the other hand, prices tend to increase in the wake of natural catastrophes due to a surge in demand for construction and repair services. These factors are included in the loss data, due to loss estimates being largely based on the cost of reinstating items that have been destroyed. As mentioned in chapter 2.3 the economic loss data are based on the figures obtained from Munich Re's NatCatSERVICE® database.[14]

The dataset obtained from the NatCatSERVICE® database comprises 113 North Atlantic storms that made landfall in the USA during the period 1950–2005. Storms that made landfall several times, i.e. where the storm returned to the open sea after initial landfall and subsequently made two or three landfalls, have been divided into their constituent events. This reflects the fact that their condition changes as they draw fresh energy from the warm sea surface. Consequently, the dataset comprises 131 storm events in all, the overall loss in the case of multiple-landfall storms being divided among the individual occurrences.

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[14] Annual loss data from the NatCatSERVICE® database are not very different from the annual loss data in Pielke Jr. (2008). In most of the years – with the exception of 1960, 1979 and 2005 – differences are not large. For some storms in particular, there are larger discrepancies, e.g. for Donna (1960) the NatCatSERVICE® provides a loss estimate of 1,250 million US$ (current US$) compared to 397 million US$ in the dataset in Pielke Jr. et al. (2008). For Katrina (2005) the NatCatSERVICE® gives a figure of 125 billion US$ compared to 107 billion US$ in the other dataset (cf. Pielke Jr. et al., 2006). Some storms are not found in both datasets.

4.4 Adjustment results

The adjustment procedure will now be explained using Hurricane Frederic (1979) as an example. Frederic made landfall on the border between Mississippi and Alabama. Florida, Kentucky, Louisiana, Maryland, Ohio, Pennsylvania, Tennessee and West Virginia were also hit. Frederic caused a loss of 6,192 million US$ (2005 values) in all. Based on 2005 values, the capital stock index in the 221 counties affected is one-and-a-half times that of 1979, i.e. the loss would have been 50% greater if Frederic had occurred in 2005. Adjusted to socio-economic conditions in 2005, the storm losses thus amount to 9,075 million US$.

Table 4.1 is a comparison of the storms that produced the highest losses. The greatest losses to date were caused by Katrina (2005) and Andrew (1992), in terms of adjusted and non-adjusted losses. Based on adjusted losses, they are followed by Donna (1960), Diane (1955), Camille (1969) und Betsy (1965), storms from preceding years. If, as is usually the case, only inflation is taken into account, Katrina and Andrew are followed by recent storms: Ivan (2004), Charley (2004), Rita (2005) and Wilma (2005).

There are also considerable differences in the loss figures for individual years. Table 4.2 shows inflation-adjusted annual losses for the period 1950–2005 and the corresponding annual figures for adjusted losses. Figure 4.3 is a graph showing annual adjusted losses. Adjustment increases the losses substantially. If inflation is taken into account only, the average annual tropical cyclone loss for the period 1950–2005 amount to approx. 7 billion US$ (2005 values). Taking the increase in the value of material assets into account, that figure rises to 10 billion US$ (2005 values).

Based on the normal inflation-adjusted figures, the years with the greatest losses were 2005, 2004, 1992, 1979, 1989 and 1972, compared with 2005, 2004, 1992, 1960, 1955 and 1965 for the adjusted loss figures. Below the top three, the order in the case of total annual losses, as with individual storms, varies considerably (see Table 4.2).

Losses adjusted by change in capital stock yield better comparability as they are no longer influenced by the varying socio-economic circumstances of the different years. Potential trends are thus no longer due to socio-economic changes. To determine whether the surmised climate-change impact is present, the loss data will now be subjected to a trend analysis.

Table 4.1: The 30 largest storms arranged in descending order by adjusted losses.

Ranking	Storm	Date	Storm category at land-fall	Losses in million US$ (US$ 2005)	Adjusted losses in million US$ (US$ 2005)	Ranking (original loss)
1	Hurricane Katrina II	29.08.2005	4	122,824	122,824	1
2	Hurricane Andrew I	24.08.1992	4	35,724	44,065	2
3	Hurricane Donna I	10.09.1960	4	4,987	34,237	19
4	Hurricane Diane	20.08.1955	TS	5,834	20,694	17
5	Hurricane Camille	17.08.1969	5	7,571	19,614	12
6	Hurricane Betsy II	10.09.1965	4	8,325	19,087	10
7	Hurricane Ivan	16.09.2004	3	18,612	18,670	3
8	Hurricane Charley I	13.08.2004	4	16,444	16,466	4
9	Hurricane Rita II	24.09.2005	3	15,851	15,851	5
10	Hurricane Hugo	21.09.1989	4	11,039	14,804	7
11	Hurricane Wilma	24.10.2005	3	14,300	14,300	6
12	Hurricane Agnes II	22.06.1972	TS	9,084	13,345	9
13	Hurricane Carla	09.09.1961	4	2,612	12,546	25
14	Hurricane Carol II	31.08.1954	2	3,172	10,526	23
15	Hurricane Frances	03.09.2004	2	9,306	9,280	8
16	Hurricane Hazel	15.10.1954	3	2,035	9,141	33
17	Hurricane Frederic	12.09.1979	4	6,192	9,075	15
18	Hurricane Alicia	17.08.1983	3	5,886	8,354	16
19	Hurricane Jeanne	15.09.2004	3	8,272	8,241	11
20	Hurricane Fran	05.09.1996	3	6,479	7,974	14
21	Hurricane Celia	03.08.1970	3	2,286	7,931	28
22	Hurricane Dora	09.09.1964	2	1,576	7,783	38
23	Tropical storm Allison	05.06.2001	TS	6,624	6,682	13
24	Hurricane Donna III	12.09.1960	2	2,267	6,126	29
25	Hurricane David I	03.09.1979	2	2,861	5,539	24
26	Hurricane Isabel	18.09.2003	2	5,310	5,308	18
27	Hurricane Donna II	12.09.1960	2	997	5,074	46
28	Hurricane Eloise	16.09.1975	3	1,997	4,760	34
29	Hurricane Georges	20.09.1998	2	4,197	4,540	21
30	Hurricane Floyd	14.09.1999	2	4,692	4,497	20

The adjacent column shows their ranking in terms of actual original loss figure. Storms that made landfall several times are divided into individual, per-landfall occurrences, each designated by a Roman numeral.

Table 4.2: Actual and adjusted annual Atlantic tropical cyclone losses in the USA, ranked by original and adjusted losses.

Year	No. of storms	Annual losses in million US$ (US$ 2005)	Annual adjusted losses in million US$ (US$ 2005)	Ranking (original annual loss)	Ranking (annual adjusted loss)
1950	1	162	3,057	35	27
1951	0	0	0	48	48
1952	0	0	0	49	49
1953	0	0	0	50	50
1954	3	5,524	21,478	17	7
1955	3	6,177	22,645	14	5

1956	1	144	811	36	32
1957	1	1,042	4,065	29	25
1958	1	47	353	41	36
1959	2	201	872	33	31
1960	1	8,251	45,437	8	4
1961	2	2,658	12,680	21	12
1962	0	0	0	51	51
1963	0	0	0	52	52
1964	4	2,427	11,793	22	13
1965	1	8,804	21,579	7	6
1966	1	42	209	44	40
1967	1	1,171	4,078	28	24
1968	1	45	224	42	38
1969	1	7,571	19,614	10	9
1970	1	2,286	7,931	23	17
1971	4	280	670	31	33
1972	1	9,348	14,111	6	11
1973	1	44	86	43	43
1974	1	99	129	39	42
1975	1	1,997	4,760	26	23
1976	1	275	388	32	35
1977	1	26	30	46	46
1978	0	0	0	53	53
1979	3	12,652	20,337	4	8
1980	2	1,424	2,404	27	29
1981	0	0	0	54	54
1982	0	0	0	55	55
1983	2	5,888	8,358	15	16
1984	2	124	254	37	37
1985	6	7,618	10,267	9	14
1986	2	107	139	38	41
1987	1	3	4	47	47
1988	5	307	405	30	34
1989	4	12,080	16,110	5	10
1990	0	0	0	56	56
1991	1	2,153	1,851	24	30
1992	1	36,915	45,497	3	3
1993	1	68	78	40	44
1994	3	2,110	2,611	25	28
1995	4	4,752	5,472	19	21
1996	3	7,252	8,779	11	15
1997	1	183	210	34	39
1998	6	7,230	7,869	12	18
1999	4	5,548	5,401	16	22
2000	2	34	36	45	45
2001	3	6,883	6,954	13	19
2002	5	3,057	3,110	20	26
2003	3	5,480	5,479	18	20
2004	6	52,853	52,876	2	2
2005	8	157,400	157,400	1	1

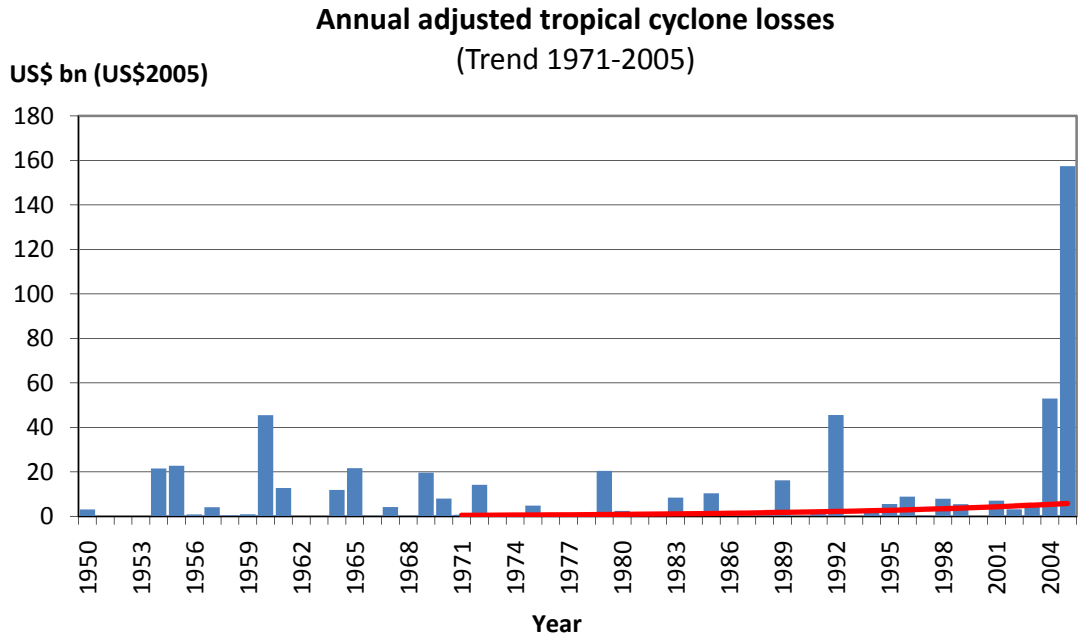

Figure 4.3: Annual adjusted Atlantic tropical cyclone losses that made landfall on the US mainland in billions of US$ (2005 values) with the 1971–2005 trend.

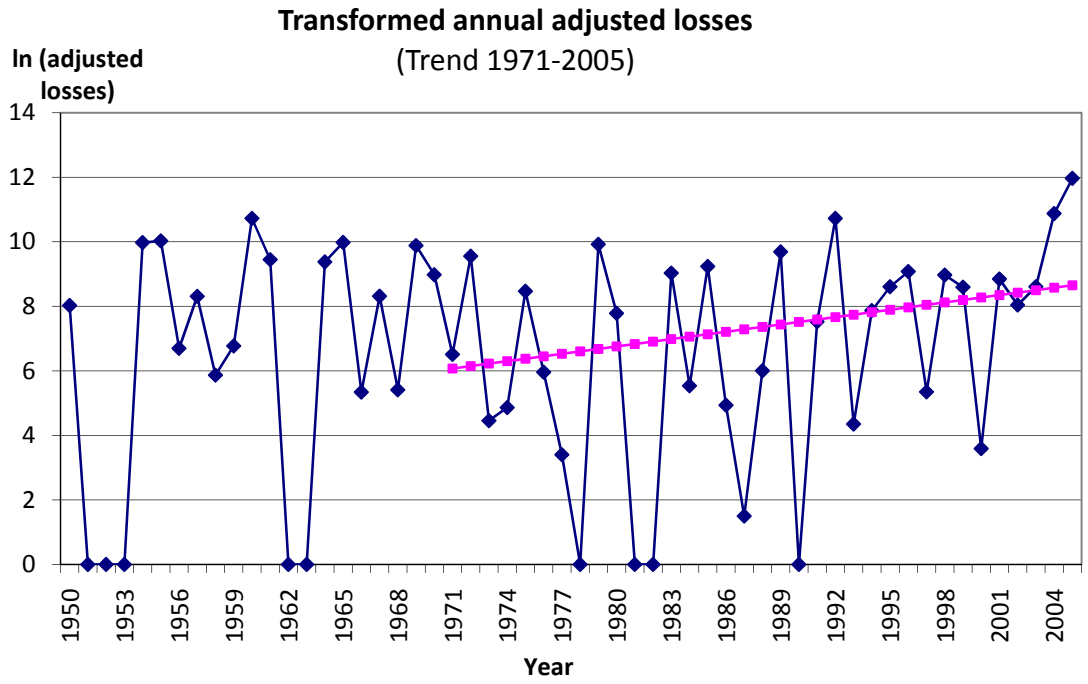

Figure 4.4: Annual adjusted losses transformed using the natural logarithm. A linear, statistically significant trend can be identified for the period 1971–2005.

4.5 Trend analysis results

Any residual trend in annual adjusted losses is determined using a linear regression. As well as performing an analysis to establish a possible trend, we also calculate the average growth rate in annual losses. Due to large fluctuations in annual losses, the growth rate is calculated on the basis of average annual loss in the respective phases of the Atlantic Multidecadal Oscillation (AMO). Phases of unusually high and unusually low sea surface temperatures lasting a number of decades can be observed in the North Atlantic. They are caused by the Atlantic Multidecadal Oscillation (AMO). Higher sea surface temperatures lead to increased cyclone activity, which then decreases in the "cold phase". The last complete "warm phase" lasted from 1926–1970, and the last "cold phase" from 1971–1994. Since 1995, the North Atlantic has been undergoing another "warm phase".[15]

The trend analysis for the period 1950–2005 yields no statistically significant trend in annual adjusted losses. Even if the two extreme years, 2004 and 2005, are omitted from the trend analysis, no trend can be identified in which the explanatory variable *time* is statistical significant. Thus, no conclusion can be drawn regarding a possible trend in the periods 1950–2005 and 1950–2003. If one take into account losses from the start of the last "cold phase" only (from 1971) one note a slight positive trend. The average annual rate of increase in adjusted losses for this period is 4%. The trend function parameters are statistically significant. Coefficient of determination (R^2) is 0.10. Figure 4.4 shows this linear trend for the logarithmised annual adjusted losses. Hurricane Katrina's exceptionally high losses (2005) would be expected to affect the average growth rate. However, if one eliminate the losses from Katrina, one still find an annual increase of 2% for the period 1971–2005, although the effect of the factor *time* is not statistical significant and the coefficient of determination (R^2) decreases to 0.089. Table 4.3 shows the regression results in detail. Losses adjusted for inflation alone increase by an average of 5% in the period 1971–2005. Excluding losses from Hurricane Katrina, the average rate of increase is around 3% per year (see Table 4.4).

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[15] Sea surface temperatures in the North Atlantic fluctuate due to the Atlantic Multidecadal Oscillation (AMO), referred to either as a "cold phase" or a "warm phase", depending on the deviation from the long-term average. Warmer phases cause greater tropical storm activity (cf. Emanuel, 2005a and Webster et al., 2005). The terms "cold phase" and "warm phase" are contested among tropical cyclone experts (cf. Goldenberg et al., 2001, Kossin and Vimont, 2007, Mann and Emanuel, 2006, Zhang and Delworth, 2006). Among those positing an AMO influence the beginning of the last "cold phase" is under discussion. The study refers to Goldenberg et al. (2001) taking 1971 as the beginning.

Table 4.3: Results of the annual adjusted loss trend analysis.

Dependent variable $\ln(loss_{2005,y})$	**Model 1 1950–2005**	**Model 2 1950–2003**	**Model 3 1971–2005**	**Model 4 1950–2005 excl. Katrina**	**Model 5 1971–2005 excl. Katrina**
Constant	7.766***	8.144***	4.402**	7.835***	4.656***
	(0.7325)	(0.7115)	(1.706)	(0.7155)	(1.664)
Time	-0.001409	-0.02006	0.07591*	-0.004825	0.06824
	(0.02140)	(0.02158)	(0.04158)	(0.02090)	(0.04055)
N:	47	45	31	47	31
R^2:	0.0001	0.0197	0.1031	0.0012	0.0890

Standard error in brackets
* denotes significance given a significance level of 10%
** denotes significance given a significance level of 5%
*** denotes significance given a significance level of 1%
Years where losses were nil have not been taken into account.

The assumption of a normal distribution of residuals is not fulfilled in Models 1, 2 and 4. Only trend model 3 is significant. For estimation purposes, initially the annual adjusted losses are transformed using the natural logarithm. Nine years in which no losses were recorded have not been taken into account. Transformed losses estimated using the ordinary least squares method are based on the following trend function:

$$\ln\big(D(y)\big) = \alpha + \beta \times time_y + \varepsilon_y$$

$D(y)$ is the annual loss in year y adjusted to economic conditions of 2005. Parameter α represents the constant. Regression parameter β shows degree and direction of influence of explanatory time trend variable $time_y$, ε_y being the error term.

Table 4.4: Average rates of increase based on average annual loss per phase of the Atlantic Multidecadal Oscillation (AMO).

	1950–2005		**1971–2005**	
	Loss in million US$ (US$ 2005)	**Adjusted loss in million US$ (US$ 2005)**	**Loss in million US$ (US$ 2005)**	**Adjusted loss in million US$ (US$ 2005)**
Average annual loss per AMO phase				
Warm phase 1950–1970[a]	2,217	8,420		
Cold phase 1971–1994			3,897	5,354
Warm phase 1995–2005[a]	22,788	23,053	22,788	23,053
Average annual rate of increase	0.04	0.02	0.05	0.04
Average annual rate of increase (excl. Katrina)	0.03	0.01	0.03	0.02

[a] The last complete "warm phase" was the period 1926–1970. Since 1995, the North Atlantic has been in another "warm phase".

The very high losses caused by Hurricane Katrina (2005) have a significant impact on the average loss figure for the current "warm phase" and thus on the average rates of increase. For this reason average annual rates of increase excluding the impact of Katrina (2005) are also given.

4.6 Discussion

The trend function is not statistical significant for the losses from 1950–2005, so that no conclusion can be drawn on a loss trend for the data over the period as a whole. However, a clear trend can be established for the period 1971–2005, losses increasing by an average of 4% per annum. This trend is shown in Figure 4.3. It was to be expected that losses would have risen on average from the start of the last "cold phase" until the current "warm phase". This is in keeping with the results of other studies on tropical storm activity. According to Emanuel (2005a), Hoyos et al. (2006), IPCC (2007a) and Webster et al. (2005) sea surface temperature correlates with storm intensity. A Munich Re study indicates that average annual adjusted losses in years where the temperature deviates from the long-term average by 0.15°C–0.45°C are around five times higher than in years where sea surface temperatures are lower (-0.45°C– -0.15°C). The losses are around 50% higher than in years where temperatures are more or less in line with the long-term average. The quantity of loss data is approximately the same for each of the three classes (Faust, 2007).[16] Average annual adjusted losses during warmer phases are thus much higher than during colder phases, an indication, at least, that natural climate fluctuations have an impact on losses. The effects of natural climate fluctuations can also be seen in Figure 4.5, the ten-year moving average of annual losses, where the adjusted losses are more or less in line with natural North Atlantic climate fluctuations.

However, the amount of loss is not only determined by natural climate fluctuations. Since losses are essentially a function of storm intensity and material assets, the area affected by the storm is also relevant. This is clearly illustrated by the year 1992 which, despite occurring in the "cold phase", is among those with the highest hurricane losses. The database records only one 1992 storm – Hurricane Andrew. Not only was it a particularly severe storm, it also affected a part of Florida with a very high concentration of material assets.[17]

Inflation-adjusted losses increased annually by 5% between the start of the last "cold phase" (1971) and 2005, whilst adjusted losses show an increase of 4% per annum over the same period.[18] Thus, the annual increase in losses cannot, for the most part, be explained by socio-economic factors over this short period of time, because natural climate fluctuations lead to great variations in losses (cf. Pielke Jr. and Landsea, 1999). The trend analysis starts at the beginning of a phase of lower cyclone activity and ends in a phase of high activity. Therefore, it is not surprising that climate-related impacts are responsible for the majority of the increase in losses.

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[16] Faust adjusted loss data from NatCatSERVICE® and from Pielke Jr. et al. (2008) using the Pielke Jr. et al. (2008) method.
[17] Hurricane Andrew was a Category 4 storm when it made landfall on the coast of Florida but it crossed the Gulf of Mexico before making a second landfall in Louisiana, again as a Category 4 windstorm. This shows that severe storms can also occur during colder phases, although they are not as frequent as in warmer phases.
[18] Were one to look at the Pielke Jr. et al. (2008) dataset over the same period, the quantitative findings would be identical (Roger Pielke Jr., personal communication).

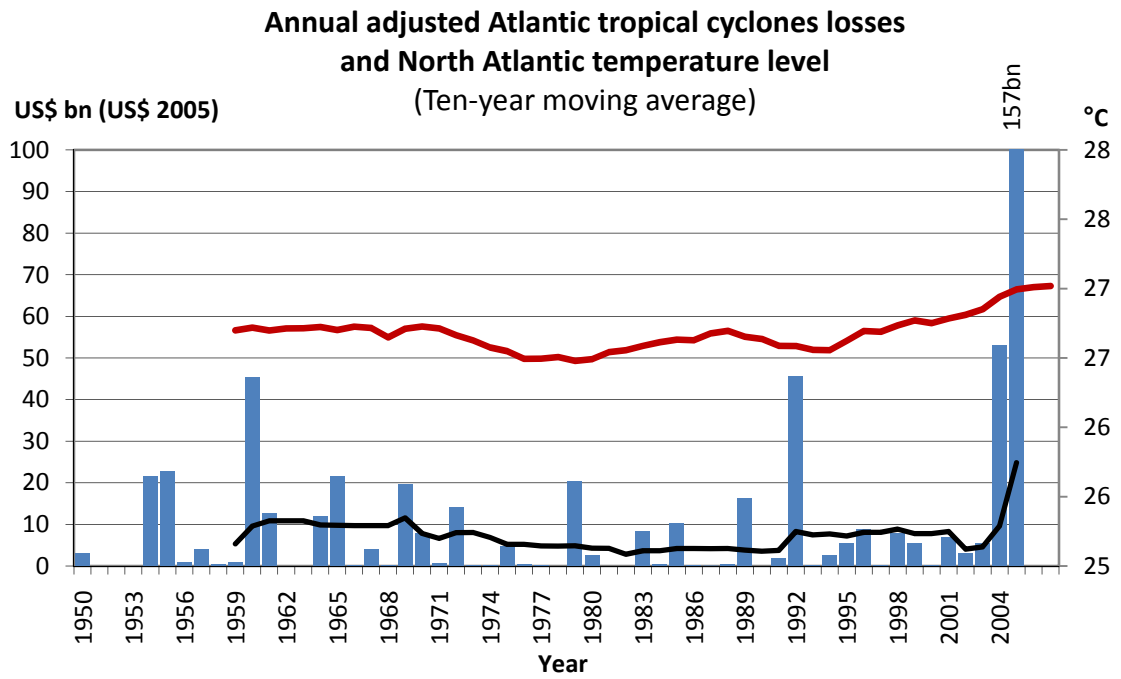

Figure 4.5: Annual adjusted losses caused by Atlantic tropical cyclones that made landfall in the USA in billions of US$ (2005 values). The ten-year average broadly follows the cycle of natural climate fluctuations (AMO) (ten-year average of mean sea surface temperature) (source of sea surface temperature: NOAA, 2007; loss data source: author).

The validity of the results is subject to a number of reservations. The relevance of the annual growth rates calculated is influenced by high annual loss volatility. The study, therefore, calculated the growth rates using the average annual loss during the different AMO phases. In addition, the assumption of a linear trend in annual loss volatility and in the cyclicity of the natural "warm and cold phases" is not entirely appropriate. This explains to some extent why the trend functions do not have high statistical explanatory power.

One also has to take into account the fact that, for the purpose of adjusting the losses, cyclone vulnerability is assumed to be constant over time. One would, however, surmise that vulnerability to weather extremes decreases as economic development increases due to higher building standards and improved disaster prevention. Sachs' (2007) study of US hurricane losses calculated loss elasticity in relation to changes in wealth to be less than one. A past storm event would, in fact, cause even greater losses today because of the higher concentrations of material assets. However, the increase in losses would not be proportional to the rise in capital stock, that stock being less vulnerable today. Nevertheless, the effect of decreasing vulnerability should not be overestimated in the case of the USA. The IPCC report argues that North America's ageing infrastructure combined with a lack of building standards or failure to enforce them are factors conducive to an ongoing rise in losses (cf. IPCC, 2007b). Miller et al. (2008) also assume a moderate reduction only in the USA's vulnerability to tropical cyclones. The situation in other parts of the world may well be different.

If constant vulnerability is assumed, the adjusted losses will be somewhat overestimated, whilst the annual growth rate in adjusted losses will tend to be underestimated. The increase in losses is therefore likely to be at least on a par with the 4% per year calculated.

The adjustment method the study has used to remove socio-economic impacts is based on the loss normalisation method described in Pielke Jr. et al. (2008), a method the study has taken a stage further. The approach described here is different from the one in Pielke Jr. et al. (2008) in three respects. Firstly, the normalised loss in Pielke Jr. et al. (2008) is established by multiplying the inflation-adjusted loss by population change and per capita change in wealth. In the approach described in this study, one do not take into account the general evolution in wealth but the value of capital stock that is at risk.

Secondly, Pielke Jr. et al. (2008) take socio-economic effects into account only in the worst hit counties, i.e. normally those located right on the coast, where storm intensity is greatest. The method presented here takes into account the whole region affected by the storm event, which comprises all the counties in which a specific wind speed is exceeded. One could assume that an approach taking into account only the counties along the coast will overestimate the loss adjustment because the growth in population and values is expected to be much higher on the US coast. But there is no large difference in the mean annual growth rate of capital stock between coastal counties only (1950–2005: 3.2%) and the exposed counties away from the coast (1950–2005: 3.1%).[19]

Thirdly, wealth differences within the USA are taken into account. This is made possible by an established database of capital stock time series for all counties located in the area affected by North Atlantic cyclones. The time series can be used to factor into the adjustment the different regional levels and differences in the rate at which the capital stock evolves, capital stock serving in our approach as an approximation of level of wealth. Wealth differences are relevant since they take into account the different wealth levels of the individual US states, a factor not addressed in the approach used by Pielke Jr. et al.. They were not able to do so because the change in per capita wealth in their approach was based on national figures relating to fixed assets and consumer durable goods (as an approximation of the level of wealth). The two methods produce different normalised or adjusted losses.

For comparison purposes, the losses taken from the NatCatSERVICE® database were again normalised using the Pielke Jr. et al. (2008) method. The study calculated the degree of normalisation for each storm in Pielke Jr. et al. (2008) by finding the ratio of normalised to nominal losses. The nominal loss for every NatCatSERVICE®-database storm was then multiplied by that factor. Four windstorms recorded in the

[19] Thanks to Joel Gratz for providing me with the list of 177 coastal counties applied in Pielke Jr. et al. (2008).

NatCatSERVICE® database could not be taken into account because they are not included in the Pielke Jr. et al. (2008) dataset.[20]

Figure 4.6 compares annual storm losses recorded in NatCatSERVICE® adjusted according to both methods. Losses normalised on the basis of the population increase in the coastal counties and national per capita wealth are higher than those adjusted to reflect change in capital stock throughout the entire region affected by the storm. If all windstorms are taken into account, the losses normalised using the Pielke Jr. et al. (2008) method are 15% higher.

The deviations are even more apparent in a number of individual cases. Thus, using the Pielke Jr. et al. (2008) normalisation factor, Donna (1960) caused a loss normalised to 2005 of around 83 billion US$, whereas the loss amount using the study's method is 45 billion US$.[21] Conversely, Flossy (1956) produces normalised losses of 462 million US$ compared with 811 million US$ using the study's method.

Whilst Pielke Jr. et al. (2008) base their normalisation on the population growth along the coast, the study presented here consider losses to be influenced by socio-economic circumstances throughout the affected region as a whole. However, this does not explain the differences in adjusted losses due to the mean socio-economic growth in the region as a whole (growth rate of capital stock at risk in the period 1950–2005: 3.1%) is nearly the same as the mean socio-economic growth along the coast (3.2%). The essential difference between the approach in Pielke Jr. et al. (2008) and the approach described here lies in the use of capital stock at risk (number of housing units and mean home value) instead of wealth at risk (population and per capita wealth) and the application of regional figures for mean home value (at state level) instead of national average on per capita wealth. As Figure 4.7 shows, all factors that normalise losses resulting from wealth at risk are higher than the factors used to adjust losses based on capital stock at risk. Figure 4.7 takes into account coastal counties only.

In view of a 15% discrepancy in the resulting annual adjusted losses between the approaches described in Pielke Jr. et al. (2008) and in this chapter, the approaches are not particularly dissimilar from each other.

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[20] There is a slight divergence in US storm data for 1950–2005 between Pielke Jr. et al. (2008) and NatCatSERVICE®. A number of storms are not found in both datasets, and have therefore not been included in the comparison: Storms Danielle (1980), Barry (1983), Arlene (2005) and Tammy (2005).
[21] The Donna loss is made up of three constituent events, referred to as Donnas I, II and III.

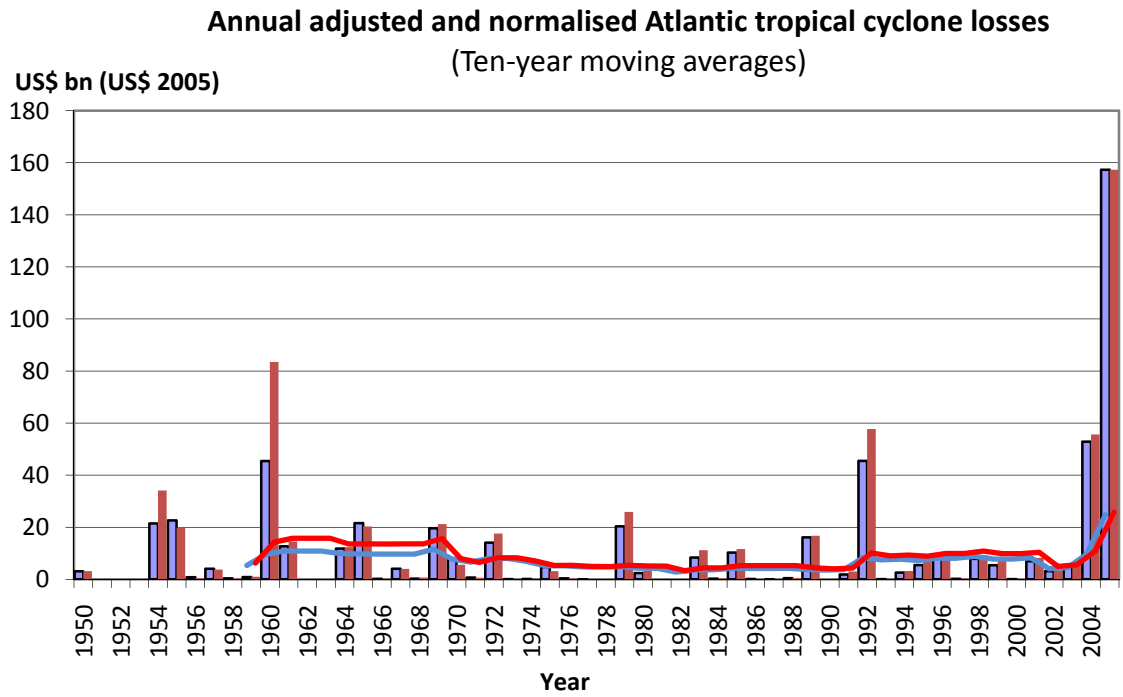

Figure 4.6: The blue columns show the annual losses adjusted by the change in the capital stock of the affected region (ten-year average in blue). The red columns show the annual losses normalised in accordance with the Pielke Jr. et al. (2008) method (ten-year average in red). The difference compared with Figures 4.3 and 4.5 is that, in this instance, only 109 windstorms are taken into account.

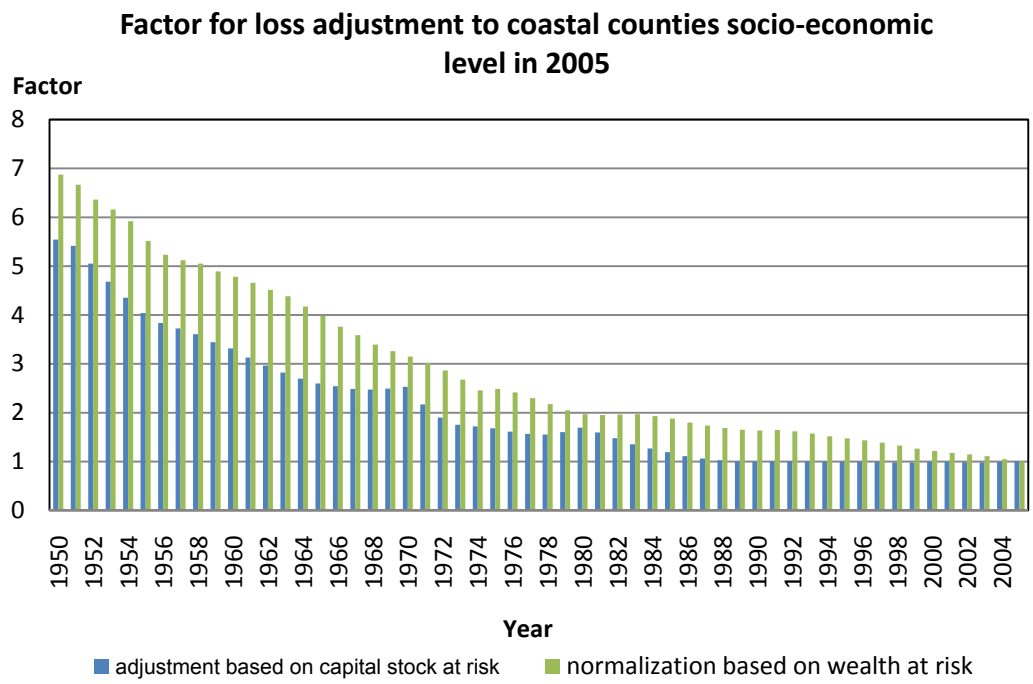

Figure 4.7: Blue bars show the factors applied for adjustment of losses to 2005 socio-economic level based on capital stock at risk (e.g. losses in year 1962 will be multiplied by factor 3). Green bars show the factors applied based on wealth at risk (population in 177 coastal counties and real wealth per capita). Losses adjusted by wealth at risk will be higher than adjusted by capital stock at risk (data source: real wealth per capita from Pielke Jr. et al., 2008; population in coastal counties as applied in Pielke Jr. et al., 2008 provided by J. Gratz; data on capital stock at risk: author).

4.7 Summary

Economic losses caused by natural catastrophes and particularly by tropical cyclones continue to increase in the USA. The issue under consideration was whether the increase in losses can be explained solely by socio-economic factors such as population and wealth increases in the regions affected or whether climate change is a substantial factor. This chapter set out to establish the potential impact that climate change as a whole (due to natural and anthropogenic forcings) has on loss trends. The IPCC states that humans have more likely than not contributed to the trend towards intense tropical cyclone activity since the 1970s. Therefore, any increase in losses could, more likely than not, be partly related to anthropogenic climate change.

The initial approach was to adjust storm losses for various years to a comparable socio-economic level before subjecting them to a trend analysis. Essentially, the following have to be taken into account:

- The generally very limited availability and quality of long-term loss data.
- The lack of a standard method for assessing natural catastrophe losses. As a result, data on a given loss vary depending on the source. Loss data from Munich Re's NatCatSERVICE® natural catastrophe database are used here. This database has used a constant evaluation method since 1974. This method is also used to evaluate pre-1974 losses.
- The assumptions made regarding adjustment to eliminate socio-economic developments have considerable impact on the results. There is no agreed method for loss normalisation yet.
- The stochastic nature of storms makes it difficult to obtain valid analyses. Depending on landfall location, region affected and the varying natural storm manifestations, annual losses can be highly volatile.

Despite these limitations, there is at least evidence to suggest that climatic change as a whole, due to both natural variability and anthropogenic forcings, does have an impact. For example, annual adjusted losses since the beginning of the last "cold phase" (1971) show a positive trend, with an average annual rise of 4% that cannot be explained by socio-economic components. This increase can at least be interpreted as a climate variability impact. There is no evidence yet of any trend in tropical cyclone losses that can be attributed directly to anthropogenic climate change. But the study advances the premise that if losses are affected by natural climate fluctuations, they are also likely to be affected by additional global warming due to anthropogenic climate change. This premise is supported by indications that the intensity of tropical cyclones is affected by anthropogenic climate change. The destructive force of tropical cyclones has been increasing globally since the mid-1970s. This increase correlates very closely with the sea surface temperature (cf. Emanuel, 2005a, Hoyos et al., 2006, IPCC, 2007a, Webster et al., 2005). According to Barnett et al. (2005) there is already a link between global warming and temperature increases in the

uppermost levels of the ocean (see also Elsner, 2006, Mann and Emanuel, 2006). They looked at the past 40 years, in which they already found a very significant impact.[22]

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[22] The sea surface temperature is not the only factor that influences intensity, however. It is possible that other factors are even more important, e.g. wind shear (cf. Bengtsson et al., 2007, Chan, 2006, Emanuel et al., 2008, Knutson and Tuleya, 2004, Wang and Lee, 2008).

5 Tropical cyclone losses sensitivities to societal and climate changes[23]

5.1 Introduction

This study investigates how sensitive economic losses caused by tropical cyclones are to socio-economic changes, in terms of increased material assets, and to climate changes, in terms of storm intensity, and how these factors have evolved over the last 50 years. The study draws an albeit approximative conclusion about the effect they may have had on historical losses. Again, in this chapter we use the term "climate change" as defined by the IPCC in its Fourth Assessment Report, i.e. "Climate change refers to any change in climate over time, whether due to natural variability or as a result of human activity" (IPCC, 2007b, 871). The study is not in a position to make quantitative statements about the separate effects of natural climate variability and human activity. According to Höppe and Pielke Jr. (2006), this question is unlikely to be settled unequivocally in the near future. Nevertheless, the impact that climate change as a whole (due to both natural and anthropogenic forcings) has on loss trends is still worth looking at in more detail. The interest in this chapter focuses on distinguishing between the signal due to socio-economic changes and the signal due to climate-related storm intensity from storm losses. This will help to understand better what is behind the observed increase in economic losses due to tropical cyclones.

The literature on the current role of climate change and of socio-economic development in US cyclone losses adopts a variety of approaches, but one problem common to all of them is the difficulty in obtaining valid quantitative results. According to Höppe and Pielke Jr. (2006), this is primarily due to the stochastic nature of weather extremes, the relative shortness and, in some cases, inferior data-quality of the available time series, and the parallel impact of socio-economic and climate-related factors on the loss data. These are the issues that have resulted in this investigation, which adopts a new approach and compares the resulting findings with those of other studies. In this way, it provides further insight into the effects of climate change on US storm losses.

Pielke Jr. et al. (2008) adopts a landmark approach in which the losses are adjusted to remove the effects of inflation, population growth and increased wealth. The authors conclude that there are no long-term trends in normalised losses. This dissertation expanded on the Pielke Jr. et al. (2008) approach in chapter 4, and noted a positive short-term trend for the period 1971–2005 that can at least be interpreted as a climate variability impact.[24] Based on this, the study in chapter 4 advanced the premise that, if the losses are affected by natural climate fluctuations, they are also likely to be affected by additional global warming due to anthropogenic climate change.

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[23] This chapter is based on a publication in Regional Environmental Change (Schmidt, Kemfert, Höppe, 2010).
[24] This short-term trend for the period 1971–2005 is confirmed by applying the dataset in Pielke Jr. et al. (2008) (see chapter 4).

This study uses another relevant approach in the literature, presented in Nordhaus (2006), to devise a method for investigating how sensitive the losses are to socio-economic and climate changes. Nordhaus depicts cyclone losses in function of intensity and society's vulnerability to cyclones. Accordingly, the more intense the destructive force of the storm and the greater society's vulnerability to disasters, the higher the losses. In his analysis, Nordhaus adjusts the loss data to remove the increase in exposed values due to economic growth, by depicting nominal storm losses in relation to US nominal gross domestic product (GDP) in the year of windstorm occurrence.[25] Nordhaus uses an econometric model to investigate the extent to which the adjusted losses are affected by maximum wind speed and time, wind speed representing storm intensity and time, vulnerability. The findings indicate that adjusted windstorm losses are highly responsive to changes in maximum wind speed.

The approach in this study is to express storm loss as a function of the value of material assets (capital stock) in the region affected, and the intensity with which those assets are impacted by the storm. Unlike Nordhaus (2006), the study incorporates the socio-economic factor directly in the loss function in the form of increased wealth based on material assets. This avoids the need to exclude socio-economic factors from the loss data. A comparable approach is described in Sachs (2007), which applies a loss function comprising wind speed, population, and per capita wealth.[26]

5.2 Method

The basic premise is that a storm loss can be expressed as a function of socio-economic and climate-related factors. Specifically, it is assumed that the economic loss can be calculated from the value of the material assets (capital stock) in the region affected by the storm and the intensity with which the storm impacts those assets. The capital stock variable represents the socio-economic components. The wind speed at landfall variable represents the intensity or climate-induced components.[27]

In fact, a number of other factors are involved such as vulnerability of assets to storm damage, surface topography, wind profile and effectiveness of disaster-prevention measures. However, in the absence of sufficient data to quantify them, the study has taken the simplified view that total asset value and wind speed only are relevant (see also Sachs, 2007).

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[25] The dataset in Nordhaus (2006) is statistically identical to that produced by Pielke Jr. et al. (2008) for the time period the two datasets overlap.

[26] Sachs (2007) also analyses US tropical cyclone losses. However, the paper does not clearly indicate on what loss data it was based and from what source they were taken.

[27] There are indications that the intensity of tropical cyclones is affected by climate change. The destructive force of tropical cyclones has been increasing globally since the mid-1970s. This correlates very closely with the sea surface temperature (SST) (cf. Emanuel, 2005a, IPCC, 2007a, and Webster et al., 2005). According to Barnett et al. (2005) there is also a correlation between SST and anthropogenic greenhouse gas emissions. The SST is not the only factor that influences intensity, however. It is possible that other factors are even more important, e.g. wind shear (cf. Bengtsson et al., 2007, Chan, 2006, Emanuel et al., 2008, Knutson and Tuleya, 2004, Vecchi et al., 2008). Climate change has an impact on various parameters like ocean temperature, atmosphere, circulation, and water vapour, and hence influences tropical storms. The processes involved are complex and not yet completely understood (cf. Wang and Lee, 2008).

The loss function to be estimated is:

$$x_j(y) = \beta \times cs_j(y)^{el_1} \times ws_j{}^{el_2} \tag{3.5}$$

$x_j(y)$ being material damage directly caused by storm j as a result of storm surge and/or wind. Flood losses are not included. Losses to offshore facilities and major installations have also been subtracted from the loss. The loss is shown in inflation-adjusted US$ (2005 values). Capital stock index $cs_j(y)$ is a proxy for the inflation-adjusted value of all material assets (2005 values) in the region affected by storm j in year y. ws_j is the maximum wind speed of storm j at landfall in knots. Parameter β is a constant. Parameters el_1 and el_2 indicate how much the loss changes if the capital stock index or wind speed change by one unit (elasticity). To determine the historical impact of climate-related changes and socio-economic effects, as a following step one need to consider the extent of climate-related and socio-economic changes in the past.

5.3 Data

The data required for the loss function are: capital stock affected, wind speed at landfall and resulting loss. To determine the capital stock affected, one first has to define the region concerned. By the definition in this dissertation, the region affected by the storm comprises all US counties where the storm caused substantial losses. This can be ascertained from the wind field, which defines the areal extent of the storm, i.e. the area in which a specific wind speed has been exceeded. For our purposes, the wind field includes all counties in which the storm was still classified as a "tropical storm", i.e., where wind speeds were at least 63 km/h. Heavy losses can occur above this limit. The wind fields are based on the Storm Track Dataset provided by the National Oceanic and Atmospheric Administration (NOAA Coastal Services Center, http://maps.csc.noaa.gov/hurricanes/download.html). The capital stock index in the relevant counties is calculated for the year of occurrence. The introduction into how to ascertain the capital stock of the relevant counties is given by chapter 2.1.

The second loss function factor is the intensity with which the storm impacts the capital stock, and for this wind speed recorded at landfall is used. Over land areas, tropical cyclones generally reach peak intensity at landfall, after which, cut off from their energy source, they gradually weaken as they move inland. The storm therefore impacts the capital stock of different counties with varying intensities, those further inland normally being exposed to lower wind speeds. For simplification purposes, the study applies wind speed at landfall to the affected region as a whole. This simplification is to be criticised. Although regional wind speed data are available, there is no information on regional losses. This makes it impossible to break losses down by wind speed and is the reason for the assumption of a uniform wind speed.

The third loss function factor is the economic loss caused by the storm. Again, economic losses are understood here to be losses to material assets as an immediate consequence of the storm. Intangible losses and indirect consequences are not included. Losses thus relate to residential, industrial and office buildings, infrastructure, building contents and moveable property in the open, e.g. vehicles are included but indirect losses are not. On the other hand, since prices tend to be driven up after natural catastrophes by a surge in demand for construction and repair services, these are included in the loss data. This is because the loss

estimates are largely based on the cost of reinstating destroyed items. As mentioned in chapter 2.3 economic loss data are based on the figures obtained from Munich Re's NatCatSERVICE® database.

The NatCatSERVICE® loss estimates also include losses at big industrial plants and offshore installations, examples being large factories, airports and oil rigs. However, the capital stock figures used in this dissertation relate only to the total value of the residential units in the counties affected, and exclude large industrial plants and offshore installations. Therefore, as far as possible, losses at large and offshore installations have been deducted from the estimated loss. NatCatSERVICE® provides this loss information for many cases of large industrial plants and offshore installations. Unfortunately, the database does not provide this loss information for smaller factories and installations. Therefore, these losses can not be deducted from the estimated loss because they are not taken into account in our capital stock index.

The NatCatSERVICE® estimates also include windstorm and storm surge losses, and flood caused by rainfall accompanying the storm. However, since equation (3.5) assumes the loss to be a function of wind speed and affected capital stock only, flood losses have, as far as possible, been subtracted from the estimated losses.[28] Information on flood losses is also taken from NatCatSERVICE® if available or from the National Flood Insurance Program (NFIP).[29]

The dataset obtained from Munich Re's NatCatSERVICE® comprises 113 North Atlantic storms that made landfall in the USA during the period 1950–2005. Storms that made landfall several times have been divided into their constituent events. Consequently, the dataset comprises 131 storm events in all, the overall loss in the case of multiple-landfall storms being divided among the individual occurrences.[30] Capital stock index in the counties affected, wind speed at landfall and windstorm and storm surge losses are available for each storm event.

5.4 Results

The following equation appears in the section describing the method:

$$x_j(y) = \beta \times cs_j(y)^{el_1} \times ws_j{}^{el_2} \tag{3.5}$$

The regression parameter values estimated for this equation are:

β = 0.0000232

el_1 = 0.441

[28] This refer to loss data in chapter 5 only. Loss figures in chapter 4 and 6 does include flood losses.

$el_2 \quad = 2.797$

Regression parameter β gives the value of the constants. Parameters el_1 and el_2 indicate by how much the loss changes if capital stock index $cs_j(y)$ or wind speed ws_j increase or decrease by one unit, el_1 showing loss elasticity relative to changes in capital stock index and el_2 loss elasticity relative to changes in intensity (in this case, wind speed). According to coefficient of determination R^2, the estimated function can account for 31% of the variance in the dependable variable $x_j(y)$.[31]

The regression results can be interpreted as follows: whereas a 1% increase in capital stock index in the region affected by the storm produces a 0.44% increase in loss, a 1% increase in wind speed produces a 2.8% increase. In other words, storm loss is far more elastic in respect of changes in wind speed than changes in capital stock index. To determine the historical impact of climate-related changes and socio-economic effects, one need to consider the extent of climate-related and socio-economic changes in the past.

Taking inflation into account, capital stock index in the states exposed to Atlantic tropical cyclones increased by an average of 3.1% per annum in the period 1950–2005. The increase for the period as a whole is 438% (see Figure 5.1). Concerning equation (3.5), the climate-related changes in the past should be measured by average annual maximum wind speed at landfall. Our dataset contains data on wind speed at landfall for just 131 storm events. That is not enough to obtain a valid average annual maximum wind speed at landfall. For many years there are records of just one or two storm events and for a few years the dataset does not contain a single event. For this reason, the development of storm intensity is calculated from the Accumulated Cyclone Energy (ACE) of all Atlantic basin storms for a given year. The ACE is an index of storm lifetime and intensity combined. It is derived from the sum of the squares of estimated maximum sustained velocity at six-hourly intervals and shown in units of 10^4 kt^2 (cf. Atlantic Oceanographic and Meteorological Laboratory (AOML), http://www.aoml.noaa.gov/hrd/tcfaq/E11.html, download 10.10.2008).[32] To be consistent with equation (3.5), the square root of ACE is used. During the period 1950–2005, storm intensity increased by 27% in absolute terms (see Figure 5.2).

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[29] The National Flood Insurance Program (NFIP) provides data about insured losses due to flood. For the purpose of considering flooding losses in the estimated overall losses, first the insured losses according to NFIP are subtracted from the insured losses in NatCatSERVICE®. Then the estimated overall losses are reduced by the same proportion.
[30] For details see chapter 2.3.
[31] Regression analysis details are shown in Table 5.1.
[32] 1 kt = 1.852 km/h.

Table 5.1: Estimation results of the storm loss function.

Dependent variable: losses due to wind	**Model 1**	**Model 2**
Constant	9.36E-09	2.32E-05
	(0.000)	(0.000)
Capital stock index	0.515	0.441
	(0.205)	(0.097)
Wind speed	4.394	2.797
	(1.126)	(0.559)
N:	130[a]	127[a b]
R^2:	0.188	0.307

Standard error in brackets.
[a] Excluding Chantal (1989) (loss due to wind = 0, flood losses only).
[b] Excluding outliers Andrew (1992), Charley (2004), Katrina (2005) (losses more than 1.5 times S.D. from mean).

Model 2, applied to the storm events of the dataset, produces an average estimated loss per windstorm of 1,455.7 million US$ (2005 values). The average observed loss was 1,424.4 million US$ (2005 values). The outliers Andrew (1992), Charley (2004) and Katrina (2005) have not been included. These outliers have been included in model 1. The coefficient of determination (R^2) however is lower and model 1 produces an average estimated loss per windstorm of 2,583 million US$ (2005 values), higher than the average observed loss.
The Levenberg-Marquardt algorithm estimates are based on the following loss function:

$$x_j(y) = \beta \times cs_j(y)^{el_1} \times ws_j{}^{el_2}$$

$x_j(y)$ being material damage directly caused by storm j as a result of storm surge and/or wind. Flood losses are not included. Losses to offshore facilities and major installations have also been subtracted from the loss. The loss is shown in inflation-adjusted US$ (2005 values). Capital stock index $cs_j(y)$ is a proxy for the inflation-adjusted value of all material assets (2005 values) in the region affected by storm j in year y. ws_j is the maximum wind speed of storm j at landfall in knots. Parameter β is a constant. Parameters el_1 and el_2 indicate how much the loss changes if the capital stock index or wind speed change by one unit (elasticity).

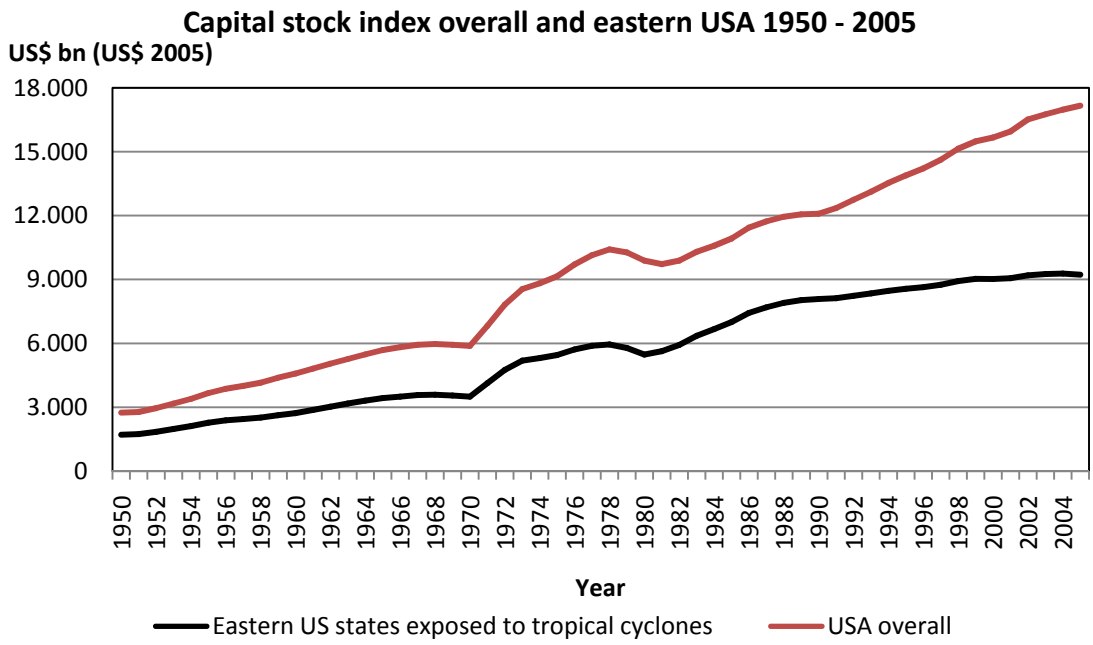

Figure 5.1: Capital stock evolution in the US states exposed to Atlantic tropical cyclones and overall US capital stock during the period 1950–2005, in inflation-adjusted billions of US$ (2005 values). Estimated capital stock index is based on the US Census of the number of housing units in the counties and the median home value in the relevant state.

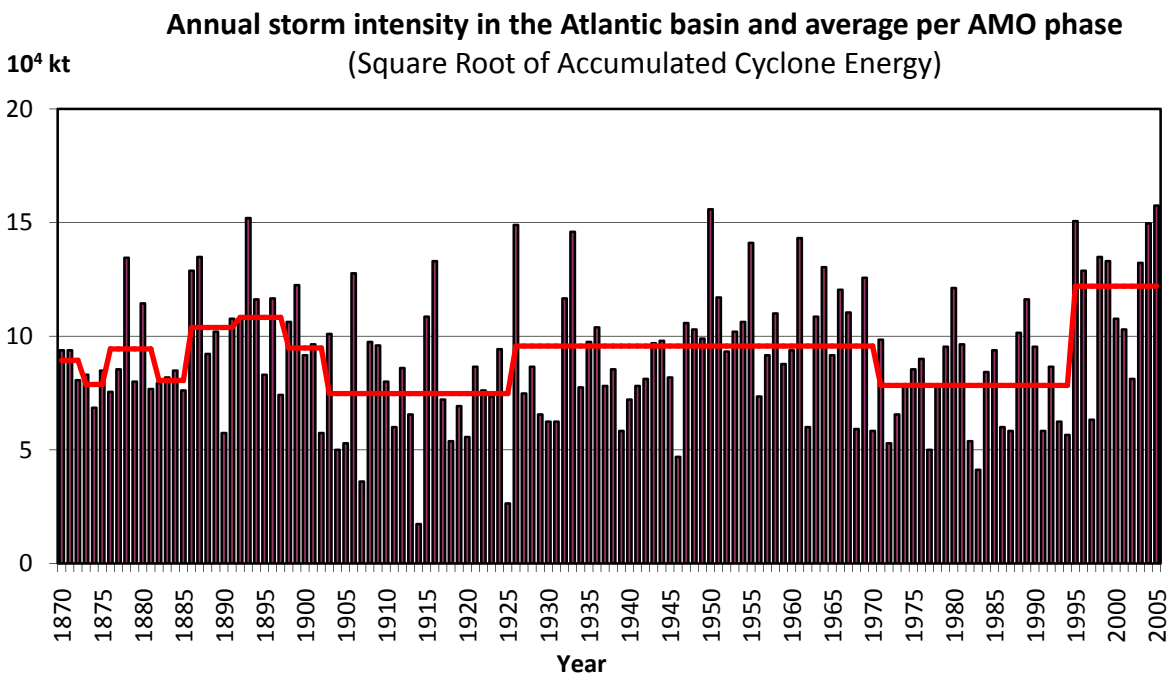

Figure 5.2: Evolution of annual tropical cyclone intensity in the period 1950–2005. The chart features all storm systems in the Atlantic basin, i.e. including those which did not make landfall (data source of ACE: Atlantic Oceanographic and Meteorological Laboratory (AOML) of the National Oceanic and Atmospheric Administration (NOAA), http://www.aoml.noaa.gov/hrd/tcfaq/E11.html, download 10.10.08; allocation of phases according to Goldenberg et al., 2001; chart: author).

Unlike the absolute growth in the capital stock index, however, restrictions are to be made regarding the robustness of the increase in storm intensity. There are two reasons for this: the high variability of the ACE and the high sensitivity of the growth rate in terms of the selected start and end points. In order to keep these influences low, the study has used the average per phase of the Atlantic Multidecadal Oscillation.[33] The 27% is therefore to be seen as the increase from the average intensity of the last "warm phase" (1926–1970) to the average intensity of the current "warm phase" (since 1995).[34] Figure 5.2 shows that since 1870 windstorm intensity has increased from each "warm phase" to the next with the exception of the two phases between 1886 and 1897. The increase in storm intensity is 0.4–5% in each case. The 27% increase in the current "warm phase" is therefore well above the long-term average. Whether this is a sign of a change in the long-term trend is uncertain because the increase will be influenced by the further development of the on-going "warm phase". This becomes apparent if the two years 2006 and 2007 are also taken into consideration. The average level of storm intensity of the current "warm phase" drops. Accordingly, the increase in storm intensity between the average of the last "warm phase" and the current "warm phase" drops to 22% (see Table 5.2).

Given an inflation-adjusted increase in capital stock index of 438% in the region investigated, and loss elasticity of 0.44 in response to a 1% change in capital stock index, it can be inferred that the loss increase due to the rise in capital stock index since 1950 was approx. 190%. Although storm intensity increased by only 27%, loss elasticity in response to a 1% change in intensity is as much as 2.8. It can therefore be concluded that the increase in losses due to greater annual storm intensity was 75%. This result depends very heavily, however, on how the intensity of the current "warm phase" develops. If the long-term increase in storm intensity of 0.4%–5% in the observation period 1950–2005 is taken as a basis, it is found that losses have increased by only 1.4%–14% as a result of the change in storm intensity. That is to say, the change in socio-economic conditions has a lower specific impact on the losses than the change in storm intensity. However, the loss trend is dominated by socio-economic conditions insofar as they changed much more than (climate-change induced) storm intensity during the investigation period.

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[33] Sea surface temperatures in the North Atlantic fluctuate due to the Atlantic Multidecadal Oscillation (AMO), referred to either as a "cold phase" or a "warm phase", depending on the deviation from the long-term average. Warmer phases cause greater tropical storm activity (cf. Emanuel, 2005a and Webster et al., 2005). The terms "cold phase" and "warm phase" are contested among tropical cyclone experts (cf. Goldenberg et al., 2001, Kossin and Vimont, 2007, Mann and Emanuel, 2006, Zhang and Delworth, 2006). Among those positing an AMO influence the beginning of the last "cold phase" is under discussion. The study refers to Goldenberg et al. (2001) taking 1971 as the beginning.

[34] Allocation of phases according to Goldenberg et al. (2001).

Table 5.2: Growth of Atlantic tropical cyclone intensity (measured in square root of Accumulated Cyclone Energy).

From	To	Growth (%)
1870–1872	1995–2005	36.4%
1926–1970	**1995–2005**	**27.5%**
1870–1872	1876–1881	5.6%
1876–1881	1886–1891	9,9%
1896–1891	1898–1902	-8.7%
1876–1881	1898–1902	0.4%
1898–1902	1926–1970	0.9%
1870–1872	1926–1970	7.0%
1870–1872	1995–2007	30.4%
1926–1970	1995–2007	21.8%

The growth is calculated on the basis of the square root of average ACE during the AMO phase. The Table includes only so-called "warm phases" (data source of Accumulated Cyclone Energy: Atlantic Oceanographic and Meteorological Laboratory (AOML) of the National Oceanic and Atmospheric Administration (NOAA), http://www.aoml.noaa.gov/hrd/tcfaq/E11.html, download 10.10.08; allocation of phases according to Goldenberg et al., 2001).

5.5 Discussion

Socio-economic developments and the impact of climate change are considered to be the primary causes of the higher tropical cyclone losses observed in the USA. Socio-economic changes largely account for the loss evolution of both tropical cyclones in the USA and weather-related natural catastrophes in general, the main reasons for this being increased wealth and greater settlement of exposed areas (cf. IPCC, 2007b), as confirmed by our results. On the other hand, the conclusions about the role of natural and anthropogenic climate change are less clear-cut. The aim of the dissertation is therefore to develop new approaches based on relevant papers taken from the literature and then compare the results with those in the literature and with each another. In this way, the dissertation will provide an additional component for determining the effects of climate change on US storm losses. The approach presented in this study is based on Nordhaus (2006). To begin with, therefore, the study will compare the results obtained using our method with the Nordhaus (2006) results.

Nordhaus depicts cyclone losses as a function of wind speed and society's vulnerability to cyclones, the analysis being based on loss data from which the increase in wealth has been subtracted. Instead of deducting increases in wealth from the losses, as is the case with Nordhaus, with our approach the impact such increases have on storm losses is included in the loss function. Thus, one can draw conclusions about the extent to which the historical loss development is due to increased wealth. Like chapter 4, the study bases changes in wealth on changes in the material assets exposed to storm (affected capital stock).

According to Nordhaus (2006), wind speed loss elasticity is 7.3, i.e. much higher than that indicated by our study and others. However, Nordhaus believes this also underestimates the true position, and suggests that 8 is more realistic.[35] Pielke Jr. (2007a) states that elasticity is 3–9, a range based on the results of a number of studies. According to our calculations, elasticity is no more than 2.8 if capital stock is also included in the loss function and losses due to flood are not taken into account. This does not, however, apply to the papers cited in Pielke Jr. (2007a) and Nordhaus (2006).

It is therefore not possible to draw a direct comparison between our conclusions on elasticity and those of Nordhaus (2006). The study therefore applied the Nordhaus (2006) method once more to our data in order to establish the reasons for the differences in elasticity. Whilst Nordhaus uses 142 storms from the period 1851–2005,[36] our data are available only from 1950. To be able to work with a comparable investigation period, the study uses Nordhaus data from the period 1950–2005 only, leaving a total of 90 storms. The wind-speed regression parameter obtained from these 90 windstorms is 7.2, an elasticity result very close to that of 7.3 obtained in Nordhaus (2006) using the complete dataset of 142 storms.[37] The number of 90 storms recorded in the Nordhaus dataset for the period 1950–2005 is considerably lower than the number of 113 storms recorded in NatCatSERVICE® over the same period, one reason for this being that Nordhaus (2006) does not include less severe storms but only those with wind speeds at or above hurricane force.

To apply the Nordhaus method to our data, one first had to base the individual storm losses on nominal GDP in the US in the year of the storm in order to remove the effects of economic growth and inflation. When one adjust our loss data in this way, the result obtained for loss elasticity to wind speed is 4.6.[38] This is still far lower than the Nordhaus (2006) result.

The datasets are not consistent. There are differences in the storms recorded and, to some extent, in the individual storm data.[39] A comparison of the loss data and wind speeds for the 78 storms recorded in both datasets reveals no major deviations. The mean loss in million US$ is 4,094.8 applying the Nordhaus dataset and 4,825.1 applying the data from NatCatSERVICE®. Mean wind speed recorded is 173.3 km/h

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[35] Nordhaus bases this on the following: wind speed is not the only factor involved; possible statistical errors in measuring wind speed, correlation of wind speed and omitted variables and the different extent to which the losses depend on building structure (cf. Nordhaus, 2006).
[36] Nordhaus' dataset for the period 1851–2005 comprises 281 storms, but includes 139 storms without any information on damage.
[37] Table 5.3 shows the regression results in detail.
[38] Details of the regression analysis are shown in Table 5.4. In our data, storms that made landfall more than once are divided into separate storm events. As Nordhaus does not make this distinction (2006), for comparison purposes, the storms have not been divided into separate events, when the study applies the Nordhaus method to its data.
[39] Twelve of the Nordhaus (2006) storms for the period 1950–2005 are not registered in NatCatSERVICE®, whilst NatCatSERVICE® includes 35 storms not recorded in Nordhaus (2006).

and 169.5 km/h respectively. If one include only the 78 storms recorded in both datasets, the loss elasticity to wind speed is 6.1 for the Nordhaus dataset and 5.0 for the NatCatSERVICE® dataset.[40]

Although the differences in the averages of the two datasets are only minor, they appear to have a distinct impact on the regression result. The sometimes large differences in the case of individual storms are likely to be significant. In line with the mean values, the dataset in Nordhaus (2006) reveals on average lower losses at higher wind speeds. Consequently, loss elasticity to wind speed is affected by the structure of the underlying dataset.

Table 5.3: Reproducing the Nordhaus (2006) results.

Dependent variable: 1n (loss/GDP)	**Model 1**	**Model 2**
Constant	-100.7*** (15.58)	-107.9*** (25.22)
1n (wind speed)	7.300*** (0.8605)	7.214*** (0.9877)
Year	0.02933*** (0.007249)	0.03317*** (0.01226)
N:	142	90
R^2	0.3557	0.3941

Model 1 includes all data for the period 1851–2005 (as in Nordhaus, 2006). Model 2 is confined to data for the period 1950–2005.
Standard error in brackets.
* denotes significance with a significance level of 10%
** denotes significance with a significance level of 5%
*** denotes significance with a significance level of 1%

Model 1 reproduces the Nordhaus (2006) results. Model 2 is confined to storms during the period 1950–2005 to allow comparison with the NatCatSERVICE® data. The estimates using the ordinary least squares method are based on the loss intensity function and data from Nordhaus (2006):

$$\ln\big(x_j(y)/GDP(y)\big) = \alpha + \beta \ln ws_j(y) + \delta year(y) + \varepsilon_j(y)$$

$x_j(y)$ being the loss caused by storm j in year y at actual prices. $ws_j(y)$ is maximum wind speed at landfall. $GDP(y)$ is US gross domestic product in year y at actual prices. $year(y)$ is the year in which the storm occurred. $\varepsilon_j(y)$ is the disturbance term.

Despite the fact that Nordhaus (2006) does not analyse the role of capital stock loss elasticity, it is necessary to discuss our result in terms of this elasticity. The fact that loss elasticity relative to changes in the capital stock index is lower than one can be interpreted to mean that housing quality is correlated with capital stock. New capital (new housing units) seems to be of better quality and is more resilient to storms.

[40] If Hurricane Katrina is excluded, because there is a large difference in estimated loss between the datasets (81 billion US$ and 125 billion US$), the mean estimated loss is 3,096.0 million US$ and 3,264.4 million US$ respectively. Mean wind speed is 173.0 km/h respectively 168.5 km/h. Loss elasticity to wind speed is 5.9 (data from Nordhaus' dataset) and 4.8 (data from NatCatSERVICE®). Tables 5.5 and 5.6 show the regression results in detail.

Nevertheless, the elasticity seems to be quite low. One reason for this could be that as a rule the capital stock index increases along with the size of the region affected. A justified objection is that the study assumes the same wind speed, i.e. the same loss intensity, for the entire region affected. This may have influenced the estimate in the following way: One windstorm that rapidly lost intensity after landfall only affected a small region. The same year, another storm that reached far inland because its intensity decreased slowly affected a much larger region. In both cases, the main losses occurred in the coastal counties. The second storm also caused further losses inland. With a much larger capital stock index, however, it goes down as the No. 1 Storm in the regression analysis. If the second storm had hit a capital stock that was 50% larger, it would have caused a loss that was larger 50%, too, based on the assumption of a constant wind speed throughout the region. In fact, however, the loss is less than 50% larger because in reality the wind speed decreases inland. This would probably lead to the loss elasticity relative to the capital stock index being lower in the calculation than it actually is. One possible way of achieving a more accurate calculation of the elasticity would be to divide the individual storms by regions with different wind speeds and to apply the losses incurred in these regions. This would require loss data at county level, but these are not available. Another option would be to include only the coastal counties in the observation. As a rule, these are the counties where the maximum wind speed is in fact likely to be recorded at landfall. This approach means that all losses are attributed to the coastal counties, however. And here, too, there are no loss data available for extracting the actual losses in the coastal counties. As this means that the capital stock index is too small compared to the losses, the estimated elasticity would be too high.

Table 5.4: Regression analysis results applying the loss intensity function from Nordhaus (2006) to the data from NatCatSERVICE®.

Dependent variable: In (loss/GDP)	**Model 3**
Constant	-24.94 (26.72)
In (wind speed)	4.608*** (0.5943)
Year	-0.002578 (0.01306)
N:	113
R^2	0.3738

Model 3 includes all storms for the period 1950–2005.
Standard error in brackets.
* denotes significance with a significance level of 10%
** denotes significance with a significance level of 5%
*** denotes significance with a significance level of 1%

Model 3 estimates the Nordhaus (2006) intensity function using the ordinary least squares method. Losses are based on NatCatSERVICE® data for 113 storms during the period 1950–2005.

Table 5.5: Regression analysis results applying the loss intensity function from Nordhaus (2006) to the 78 identical storms in the Nordhaus and the NatCatSERVICE® dataset with losses from Nordhaus (2006).

Dependent variable: In (loss/GDP)	**Model 4**	**Model 5**
Constant	-36.76**	-36.11**
	(4.341)	(4.306)
In (wind speed)	6.082**	5.930**
	(0.9605)	(0.9534)
N:	78	77
R^2	0.3368	0.3315

Model 4 includes all storms for the period 1950–2005 recorded in both databases.
Model 5 Katrina 2005 is excluded.
Because *year* is tested to be not significant it is not included.
Standard error in brackets.
* denotes significance with a significance level of 10%
** denotes significance with a significance level of 5%
*** denotes significance with a significance level of 1%

Model 4 and Model 5 estimates the Nordhaus (2006) intensity function using the ordinary least squares method. Losses are based on Nordhaus (2006) for 78 identical storms during the period 1950–2005 recorded in the NatCatSERVICE® too.

Table 5.6: Regression analysis results applying the loss intensity function from Nordhaus (2006) to the 78 identical storms in the Nordhaus and the NatCatSERVICE® dataset with losses from NatCatSERVICE®.

Dependent variable: In (loss/GDP)	**Model 6**	**Model 7**
Constant	-31.86**	-30.96**
	(3.700)	(3.703)
In (wind speed)	5.042**	4.833**
	(0.8245)	(0.8259)
N:	78	77
R^2	0.3210	0.3043

Model 6 includes all storms for the period 1950–2005 recorded in both databases.
Model 7 Katrina 2005 is excluded.
Because *year* is tested to be not significant it is not included.
Standard error in brackets.
* denotes significance with a significance level of 10%
** denotes significance with a significance level of 5%
*** denotes significance with a significance level of 1%

Model 6 and Model 7 estimates the Nordhaus (2006) intensity function using the ordinary least squares method. Losses are based on NatCatSERVICE® for 78 identical storms during the period 1950–2005 recorded in Nordhaus (2006) too.

Although the findings reported in this study on the role of socio-economic effects and climate-related factors in the loss increase of recent decades differ somewhat from chapter 4, the assumption that climate-related changes positively influence losses is confirmed. In chapter 4 a method based on the "Normalized Hurricane Damages" approach put forward by Pielke Jr. et al. (2008), and Pielke Jr. and Landsea (1998) is used. Pielke Jr. et al. (2008) adjust the losses to remove the effects of inflation, population changes and per capita wealth. Normalisation is based on changes at the coast only. The authors conclude that there is no long-term trend in normalised losses. Chapter 4 took this method a stage further and adjusted the losses to subtract increased wealth in terms of material assets. At the same time, changes in material assets (capital stock index) were based on all the counties affected by the storm, so that the different levels of wealth inland and between individual states were also taken into account.

The adjusted individual losses were then collated to show annual adjusted losses, and a time-series analysis performed. Any remaining trend in these adjusted losses cannot be ascribed to socio-economic developments. A positive but not significant trend was identified for the period 1950–2005. However, a positive, statistically significant trend was identified for the period from the start of the last "cold phase" (1971) until 2005. Annual adjusted losses increased on average by 4% during this period compared with 5% for annual losses adjusted to exclude inflation but not greater wealth.[41] Due to large fluctuations in annual losses, the annual growth rates were calculated on the basis of average annual loss in the respective phases of the Atlantic Multidecadal Oscillation. The current study analyses the loss data using a different method. The technique used in chapter 4 allows one to draw indirect conclusions only about the impact of climate changes, the losses being adjusted solely to exclude increases in wealth (see chapter 4 regarding adjustment inaccuracies). Climate change is just one of a number of other factors that may impact losses. Changes in society's vulnerability to storms, another factor not included in the adjustment and therefore still reflected in the loss data, can thus be assumed to have a bearing on any trend in the adjusted losses. The current study does not use losses adjusted to reflect changes in wealth. Instead it establishes the sensitivity of storm losses to changes in socio-economic effects and climate-induced storm intensity, and the manner in which these factors have developed historically. The historical impact of socio-economic effects and climate-related change on the losses can then be deduced by combining relative loss change, based on a change in the relevant factor, with the change in those factors observed during past decades in absolute terms. Thus, instead of eliminating the influence of socio-economic factors, as was the case with chapter 4, in this approach they are explicitly included. Although shortcomings also have to be taken into account when interpreting the results obtained with the approach presented here, it is a more apposite way of explaining the impact of socio-economic effects and climate-related change on US storm losses.

[41] Were one to look at the Pielke Jr. et al. (2008) dataset over the same period, the quantitative findings would be identical.

5.6 Summary

The objective of this chapter was to establish how sensitive tropical cyclone losses are to socio-economic and climate changes and how these factors have evolved in the last 50 years. Conclusions have been drawn about the part the factors play in the observed increase in losses. The results show that, historically, the increase in losses due to socio-economic changes was approximately three times higher than that due to climate-induced changes.

It should be noted when assessing the results of both this chapter and chapter 4 that it is generally difficult to obtain valid quantitative findings about the role of socio-economic effects and climate change in loss increases. This is because of criteria such as the stochastic nature of weather extremes, a shortage of quality data, and the role of various other potential factors that act in parallel and interact. Both studies therefore regard the results as being an indication only of the extent to which socio-economic and climate changes account for the increase in losses. Both studies confirm the consensus reached in May 2006 at the international workshop in Hohenkammer attended by leading experts on climate change and natural catastrophe losses (see Table 5.7).

Seen from the insurance industry's perspective, the loss evolution and the principal factors influencing it can be summarised as follows: rising loss figures due to socio-economic developments do not generally cause problems for insurers, since the linear nature of the increase in premiums and sums insured (i.e. capital stock) ensures that the effective loss ratio remains constant. However, this does not apply to increases driven by storm intensity. To prevent rising loss ratios, the premium would have to be recalculated to take account of the changes in the underlying parameters. Without this, the insurer would face growing losses. This study believes that this paper's findings on the role climate-related change plays in the increased losses confirms that insurance industry models should take this factor into account (see also Faust, 2002a).

Table 5.7: Consensus and recommendations of the international workshop held at Hohenkammer in Germany on 25 and 26 May 2006 and attended by leading experts on climate change and natural catastrophe losses (source: Bouwer et al., 2007, supporting online material: www.sciencemag.org/cgi/content/full/318/5851/753/DC1).

Consensus (unanimous) statements of the workshop participants

1. Climate change is real, and has a significant human component related to greenhouse gases.
2. Direct economic losses of global disasters have increased in recent decades, with particularly large increases since the 1980s.
3. The increases in disaster losses primarily result from weather-related events, in particular storms and floods.
4. Climate change and variability are factors which influence disaster trends.
5. Although there are peer reviewed papers indicating storm and flood trends, there is still scientific debate over attribution to anthropogenic climate change or natural climate variability. There is also concern about geophysical data quality.
6. IPCC (2001) did not achieve detection and attribution of extreme event trends at global level.
7. High-quality, long-term disaster loss records exist, some of which are suitable for research purposes, such as identifying the effects of climate and/or climate change on loss records.
8. Analyses of long-term records of disaster losses indicate that societal change and economic development are the principal factors behind documented increasing losses to date.
9. The vulnerability of communities to natural disasters is determined by their economic development and other social characteristics.
10. There is evidence that the changing patterns of extreme events are drivers of recent increases in global losses.
11. Due to data-quality issues, the stochastic nature of extreme event impacts, the lengths of the time series, and various societal factors present in the disaster loss records, it is still not possible to determine what portion of the increase in damage may be due to climate changes caused by GHG emissions.
12. For future decades, the IPCC (2001) expects there to be increases in the frequency and/or intensity of some extreme events as a result of anthropogenic climate change. In the absence of disaster reduction measures, such increases will cause a further rise in losses.
13. The quantitative link (attribution) between storm/flood loss trends and GHG-induced climate changes is unlikely to be determined unequivocally in the near future.

Policy implications identified by the workshop participants

14. Adaptation to extreme weather events should play a central role in reducing societal vulnerabilities to climate and climate change.
15. Mitigation of GHG emissions should also play a central role in response to anthropogenic climate change, although it will have no effect on the hazard risk for several decades.
16. We recommend further research on different combinations of adaptation and mitigation policy.
17. We recommend the creation of an open source disaster catalogue of agreed standards.
18. In addition to fundamental research on climate, research priorities should consider decision-makers' needs in terms of adaptation and mitigation.
19. To better understand loss trends, there is an ongoing need to collect and improve the long-term (paleo) data and create homogenous climate and disaster-loss datasets.
20. The community needs to agree on peer-reviewed procedures for normalising economic loss data.

6 Simulation of economic losses from tropical cyclones in the years 2015 and 2050 – the effects of anthropogenic climate change and growing wealth[42]

6.1 Introduction

Since the severe storm losses in 2004 and 2005, there has been increasing speculation in the media and in the scientific world about the losses that may be expected from tropical cyclones in the future and about the role that human-induced climate change may play in this context. However, the question of what additional losses can be expected due to socio-economic trends is only seldom discussed. In other words, what will be the trends in population and material assets, and their geographical distribution in the regions impacted by storms, and what will be their impact on losses. Even more than anthropogenic climate change, it has to be expected that future increases in population and in the assets threatened by storms will lead to loss increases. This chapter shows that the principle loss drivers in the future will continue to be socio-economic ones. Nevertheless, anthropogenic climate change will also lead to noticeable loss increases.

Three influencing factors need to be analysed if we are to answer the question of how future costs for tropical cyclones will develop. Firstly, the change in the risk situation that may result from climate change. In other words, the change in frequency and regional distribution of the storms, as well as any increase in their intensity. Secondly, any change in the susceptibility to storms of people and material assets, or what is known as their vulnerability. Thirdly, we need to analyse at the increase in material assets and population that is at risk from the storms, or what is known as exposure.

The simulations in this study are based on a stochastic model that simulates an average annual loss. The model comprises two components. The first component determines the number of storms` in a particular year. The second component determines the loss for each of these storms. The annual loss is obtained from the number of storms and the individual loss per storm, as the sum of two random processes. The high variability in the annual storm loss that can be seen in reality is thus simulated through the variation in the number of storms per year and the variation in the individual loss. By way of example, the model is applied to losses from tropical cyclones in the USA. An average annual storm loss is simulated for the US coastline along the Atlantic and Gulf of Mexico, such as might arise under the conditions expected for the years 2015 and 2050. The conditions for future storm losses are determined by assumptions about the increase in material assets in the cyclone-prone regions (exposure), as well as assumptions about the change in the risk situation (frequency and intensity of the cyclones) as the result of global warming. The susceptibility of the exposed material assets to cyclones (vulnerability) is assumed to remain constant. A

[42] This chapter is based on a submission to Global Environmental Change (Schmidt, Kemfert, Faust, 2009).

supplementary analysis simulates the average annual loss that results for three different storm categories: light, weak to moderate, and strong to devastating.

On the one hand, this chapter provides an additional module for research into the additional costs of tropical storms caused by anthropogenic climate change. In addition, it addresses the question of the overall cost of future storms, both as a result of anthropogenic climate change, and from the future increase in material assets in the storm-prone regions. The IPCC believes the increase in material assets will represent a key factor for future storm losses (cf. IPCC, 2007b). However, apart from Pielke Jr. (2007a), and Pielke Jr. et al. (2000), no quantitative studies have been carried out up to now.

6.2 Overview of the status of research

In order to answer the question of what loss amount could result from tropical cyclones in the year 2015, or 2050, assumptions need to be made about the change in the risk situation (frequency, regional distribution and intensity of storms), the level of and change in susceptibility to such storms (vulnerability), and the change in material assets at risk from the storms (exposure situation).

6.2.1 Change in the risk situation

The risk situation from tropical cyclones covers their occurrence (frequency and regional distribution) and the intensity of the storms. Among other things, climate change affects ocean temperature, the atmosphere, and the circulation and evaporation of water. The changes it gives rise to could affect tropical cyclones. However, the relationships are complex and are not fully understood at this point in time (cf. Wang and Lee, 2008).

For example, there is no current consensus on how the global number of tropical cyclones might change as a result of global warming (cf. IPCC, 2007a, Knutson et al., 2008, WMO, 2006). The results of a survey of storm experts conducted by Pielke Jr. (2007a) on the expected change in frequency for 2100 (2050) range from a predicted 40% (20%) reduction to a 40% (20%) increase. For the Atlantic, Bengtsson et al. (2007) expect the frequency of the storms to remain constant (see also IPCC, 2007a). In contrast, Emanuel et al. (2008) calculated a slight increase in the number of storms in the Atlantic. Similarly, there has been no consensus so far among storm experts on what changes might occur in the tracks of tropical storms, or what shifts there might be in the regions affected (cf. WMO, 2006).

On the other hand, there are clearer indications that global warming is leading to an intensification of the storms. For example, the destructive force of tropical storms in most of the oceans has been increasing since the mid 1970s. This increase correlates strongly with the sea surface temperature (cf. Emanuel, 2005a, Hoyos et al., 2006, IPCC, 2007a, Webster et al., 2005). According to Barnett et al. (2005), there is in turn a connection between sea surface temperature and anthropogenic emissions of greenhouse gases (see also Elsner, 2006, Mann and Emanuel, 2006). Barnett et al. have already been able to determine a very significant impact over the last 40 years. If the oceans continue to warm up, storms may therefore be expected to become more intense (cf. IPCC, 2007a, WMO, 2006). However, the sea surface temperature

is not the only factor that influences intensity. Other factors, such as wind shear, may even be more significant. If this is factored in, the result for the Atlantic by the end of the 21st century is a 7.4% increase in intensity (Emanuel et al., 2008), or an increase in wind speeds of roughly 6% (Bengtsson et al., 2007, Knutson and Tuleya, 2004).[43] According to Vecchi et al. (2008), with anthropogenic climate change, the interaction between the ocean basins on a global scale is crucial for understanding the effects in the tropical Atlantic. With this approach, the overall effect of Atlantic storm activity actually remains unchanged, because the different factors cancel one another out. Predictions about the change in intensity among the storm experts interviewed in Pielke Jr. (2007a) vary from 0% to 36% (0%–18%) for the year 2100 (2050).

6.2.2 Change in vulnerability

Vulnerability denotes how susceptible people and material assets are to storms. It indicates, for example, how well early warning systems and catastrophe prevention measures operate. But it also looks at how well construction standards are implemented for risks from storms, rain and storm surge. The impact of hurricane Katrina in August 2005 illustrates the vulnerability of infrastructure and municipal systems, whose safety standards proved inadequate to cope with this event (cf. IPCC, 2007b).

The degree of change in loss for just a marginal change in wind speed clearly shows how susceptible people and material assets are in the face of storms. The loss susceptibility can be thought of as the elasticity of losses to wind speed (see chapter 5). In equation 6.1, this elasticity is determined via the parameter *el* in the loss function based on Howard et al. (1972).

$$x_j = \alpha \times ws_j^{el} \tag{6.1}$$

The loss x_j from storm j is a function of wind speed ws_j. α is a constant, *el* is the parameter for elasticity.

There are various estimates in the literature for the degree of this elasticity *el*. Earlier economic papers, such as those incorporated in the Second Assessment Report of the IPCC, assume low elasticity. Cline (1992) assumes a linear increase in the loss relative to wind speed. Fankhauser (1995), on the other hand, anticipates a 1.5-fold increase. In Tol (1995), the loss increases by two units for every one-unit increase in wind speed. More recent economic papers assume higher elasticity. The correlation between wind speed and loss should at least correspond to a cubic function (cf. Hallegatte, 2007a, Stern et al., 2006 and chapter 5). Howard et al. (1972) arrive at a figure of 4.36. Nordhaus (2006) quotes insurance studies that assume a elasticity of between 4 and 6, while he himself calculates elasticity as 8.

The level of elasticity changes over time since vulnerability changes too. However, it is difficult to quantify this change. Vulnerability is subject to very different influences, which in some cases have opposite effects. One example of this is the improvement in building construction standards and the simultaneous

[43] In addition to maximum wind speeds, intensity also encompasses the duration of the storms.

increase in settlement in the storm-prone coastal areas. Hallegatte (2007a) finds for the USA that there is a general increase in vulnerability over time, but that there is a reduction after a storm has struck. However, Jain et al. (2005) illustrate that the vulnerability of buildings decreases over time. This indicates that an improvement in construction standards positively influences the loss susceptibility of the buildings.

Pielke Jr. (2007a) assumes constant vulnerability over time. Thus a twofold increase in the material assets affected by storms results in a doubling of the losses. In view of the complexity of the subject of vulnerability, many economic studies assuming constant vulnerability (see for example Cline, 1992, Fankhauser, 1995, Nordhaus, 1996, Tol, 1995). We shall adopt the same approach in this chapter.

6.2.3 Change in material assets at risk (exposure)

The size of direct economic storm losses depends primarily on the volume of material assets in the region affected by the storm. In turn, the amount of material assets at risk from storms basically depends on trends in population figures, the economic wealth, and settlement distribution.

There have been very few quantitative analyses so far to determine the extent to which such socio-economic trends will contribute in future to additional losses. The main focus of research has been clearly on the additional cost of anthropogenic climate change. Admittedly, the IPCC believes that the increase in material assets exposed to tropical storms represents a key factor for future losses (cf. IPCC, 2007b). However, an estimate of such additional costs can only be found in Pielke Jr. et al. (2000), and Pielke Jr. (2007a). In his 2007 study, Pielke Jr. applies two scenarios. The scenario with a slow increase in population and wealth assumes that the population and level of wealth in the region threatened by storms will be higher by a factor of 2.8 in 2050 compared to 2006. For the scenario with more rapid socio-economic development, a level is assumed that is seven times higher. These assumptions about the level are with annual socio-economic growth of 2.5% or of 4.9%.[44] Average estimates for the future expect the world population to increase by 1% and the per capita gross domestic product (GDP) by approximately 2.5% per annum. This gives annual socio-economic growth of 3.5%, a value that lies between the two scenarios (cf. Pielke Jr., 2007a). The empirical data the author uses on population and wealth in the storm-prone coastal countries of the US give a growth figure for population and wealth for the period 1950–2005 of 4.1% per year (without inflation) (cf. Pielke Jr., 2007a).[45]

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[44] As is usual, no account is taken of the effect of inflation. The figures in Pielke Jr. (2007a) are in 2006 US$ prices (2006 values).

[45] Official data is only available for population trends in the counties of the USA, but not for the trend in economic wealth (Bureau of Economic Analysis, in writing 23.08.2006). Pielke Jr. therefore bases the calculation of the combined growth in population and wealth in the coastal regions on data on the national per capita level of wealth (cf. Pielke and Landsea, 1998, Pielke Jr. et al., 2008).

6.3 Method

A stochastic model that calculates an average annual loss from a large number of generated annual losses is used as the basis for the simulations in this paper. The model consists of two components. The first component determines the number of loss events. In our case, this is the number of storms in the space of a year. The second component determines the individual loss amount for each of the separate loss events. This represents the loss per storm. The annual loss is obtained from the number of events and the individual loss per event, as the sum of two independent random processes. The high variability in the annual storm loss that can be observed in reality is thus recreated through the variation in the annual number of storms, and the variation in the individual loss. The model described here is similar to a model presented by Katz (2002a) for simulating tropical storm losses. Rootzén and Tajvidi (1997) applied a comparable method for extratropical storm losses.

6.3.1 Model description

Frequency

The number of cyclones is characterised by the random variable *N(t)*, with the random number of storms within the time interval [0;*t*]. It is assumed that the random variable *N(t)* is Poisson distributed (cf. also Katz, 2002a, Nordhaus, 2006, Hallegatte, 2007a).

Loss per storm

The random variable $X_k > 0$ represents the loss that is caused by the *k*-th storm within the time interval. In reality, it can be observed that many storm events occur with small losses, while just a small number of storm events can cause major losses. This implies that the frequency distribution of the losses follows a distribution similar to lognormal distribution. This is also assumed for the distribution *F* of the random variable X_k.

Annual loss

The loss from all storms within the time interval [0;*t*] is the total of losses for the individual storm events. For a time interval of one year, this annual loss is *D(t)*:

$$D(t) = X_1 + X_2 + \cdots + X_{N(t)};\ N(t) \geq 1; \text{otherwise}\ D(t) = 0 \tag{3.8}$$

6.3.2 Model estimate

Description of the data

For the estimation of the model parameters, a dataset of observed storms was used from the Munich Reinsurance NatCatSERVICE®. For the period 1950–2005, the NatCatSERVICE® recorded 113 North Atlantic storms that caused losses on the US mainland. Some of these storms made landfall several times. In

other words, after its first landfall, the storm moved back out over the open sea. After that, it made landfall a second time, and sometimes a third time, in a different location. These storms are divided into separate storm events, since the state of the storm changes due to the renewed energy it derives from the warm surface layers of ocean water. The dataset used therefore encompasses a total of 131 storm events. In the case of storms with multiple landfall, the total loss is distributed among the different storm events.[46]

The losses from the individual 131 storm events are adjusted to the socio-economic conditions of the year 2005. This allows us to eliminate the influence that inflation and changes in population and wealth have on losses over time. The loss data are therefore in US$ prices from 2005 and at the level of wealth in 2005. In other words, the losses are given as if all 131 storms had occurred in the year 2005. The loss $x_k(y)$ required for the parameter estimate is obtained by adjusting the inflation-adjusted loss $x_j(y)$ caused by storm j in the year y. For this, the inflation-adjusted loss $x_j(y)$ is multiplied by the ratio between the capital stock in the year 2005 in the region affected by storm j, denoted as $cs_j(2005)$, and the inflation-adjusted capital stock in the same region in the year y, denoted as $cs_j(y)$. The capital stock encompasses the value of all material assets in the region affected.

$$x_k(y) = x_j(y) \times cs_j(2005) \div cs_j(y) \tag{3.1}$$

Following the adjustment, there is an adjusted loss $x_k(y)$ for each loss $x_j(y)$ that is at the level of wealth in the year 2005.[47]

Estimate of model parameters and simulation of basic scenario

In the period 1950–2005, the dataset recorded 131 storm events. This gives an average of 2.34 storms per year. The average loss per storm is 4,266 million US$ (in the prices and at the level of wealth in 2005). Table 6.1 contains statistical values for the distribution of frequency, the average annual loss and the loss per storm event.

Using these model parameters as a basis, we simulate the annual storm loss for 10,000 years with a Monte Carlo simulation. Table 6.2 shows the results of the simulation. Our model can adequately explain the annual number of storms and the average annual loss observed. The simulated average annual loss, at 9,136 million US$ (in 2005 prices) was slightly below the observed average annual loss of 9,980 million US$ (in 2005 prices).

The following section now applies this model to simulate the average annual loss while incorporating assumptions on climate-driven and socio-economic changes.

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[46] For details see chapter 2.3.
[47] See chapter 4 for a detailed description of adjusting storm losses for socio-economic developments. For an alternative approach, also see Pielke Jr. et al. (2008).

Table 6.1: Distribution of frequency, annual loss and loss per storm for the 131 storms in the dataset.

	N	Mean	S.D.	Min.	Max.
Frequency	56	2.34	2.16	0	10
Annual loss in million US$ (US$ 2005)	56	9,980.3	23,250.3	0	157,400.1
Loss per storm in million US$ (US$ 2005)	131	4,266.4	12,311.7	0.05	122,824.3

Table 6.2: Results of the Monte Carlo simulation of frequency and annual loss in the dataset (baseline scenario).

	N	Mean	S.D.	Min	Max
Frequency	10,000	2.31	1.53	0	10
Annual loss in million US$ (US$ 2005)	10,000	9,135.8	13,781.7	0	135,360.8

6.4 Simulation of the average annual loss for 2050 and 2015

First of all, the assumptions on the three influencing components are described: the risk situation, the loss elasticity to wind speed (vulnerability) and the material assets at risk. Next, the assumptions are transferred to the frequency distributions used in the simulations for the number of storms and the individual loss amount. After that, the results of the simulations are presented. The section begins with the longer-term perspective (simulation for 2050). The assumptions and results for the medium-term perspective (simulation for 2015) are then supplemented.

6.4.1 Assumption on change in risk situation (frequency and intensity)

While we believe that a change in frequency is possible as a result of anthropogenic climate change, our simulations are based on the assumption that there will be no change in frequency as long as no consensus has been reached on this matter (see section 6.2.1 status of research). That's in agreement with Pielke Jr.

(2007a) and Nordhaus (2006). As regards intensity, it is assumed that the maximum wind speeds will increase by 3% up to the year 2050.[48] The assumption is based on Bengtsson et al. (2007), who calculated a 6% increase in the maximum wind speeds by the end of the 21st century in comparison with the end of the 20th century. This is based on an emission scenario where no climate protection measures are taken (SRES A1 scenario of the IPCC, cf. Nakicenovic et al. 2000). For the assumption on the year 2050, the increase in wind speeds determined by Bengtsson et al. (2007) is halved. The associated assumption of a linear increase in wind speeds was taken for reasons of simplification.[49]

In the simulations, no allowance is made for the influence of the natural variation in climate known as the Atlantic Multidecadal Oscillation (AMO). In the course of the natural fluctuation in the sea surface temperature, there is a change in both the intensity and the frequency of storms in the North Atlantic.

6.4.2 Assumption on loss elasticity and the change in it over time (vulnerability)

The loss function (see equation 6.1) assumes a loss elasticity to wind speed of 3 (as does Hallegatte, 2007a, Pielke Jr., 2007a, and Stern et al., 2006). An elasticity of 3 must be seen as a conservative assumption. Pielke Jr. (2007a) also makes allowance for scenarios with elasticity of 6 and 9, while Nordhaus (2006) calculates an elasticity of 8.

As described in the section on the status of research, it is extremely difficult to quantify the change in loss susceptibility (vulnerability) over time. In the simulations, we therefore assume that there is no change in loss elasticity to wind speed. The loss from a storm thus increases proportionally to the increase in the level of material assets affected by the storm.

6.4.3 Assumption on the change in the level of material assets at risk

For the year 2050, we assume that the capital stock in the eastern states of the USA that are affected by North Atlantic cyclones is 297% higher than it was in 2005. This increase by a factor of four results if we assume an annual increase in capital stock of 3.1% (excluding inflation). In the period between 1950 and 2005, after adjustment for inflation, the capital stock increased by an average of 3.1%. It is assumed that this average growth will continue in the future.

No data on regional capital stocks is available for the USA. For the period 1950 to 2005, we have therefore made an approximate calculation of the capital stock in each case based on the number of housing units in the US counties affected and their average value in 2005 US$ prices.[50]

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[48] The maximum wind speed is the average of the wind measurements within one minute.
[49] Bengtsson et al. (2007) make no statement on the form of the increase in wind speed by the end of the 21st century.
[50] For a detailed description and discussion of the calculation of the capital stock, see chapter 2.1.

6.4.4 Transferring the assumptions to the model

As a result of global warming, maximum wind speeds will increase by 3% by the year 2050. The frequency distribution F of the random variable X_k (loss per storm) has been shifted accordingly. This gives the new frequency distribution, as affected by anthropogenic climate change, for the storm loss F_{cc}:

$$F_{cc} = F \times (1 + cc)^3 \tag{6.2}$$

The parameter cc stands for the change in wind speed resulting from climate change and is 0.03. Due to the assumed elasticity of 3, the frequency distribution F shifts by a factor of 1.093 to the new distribution F_{cc}. This modified frequency distribution is used for the simulation of the average annual loss resulting from climate change in 2050. The frequency distribution of the random variable $N(t)$ was left unchanged. The variable $N(t)$ stands for the number of storms per year.

Since we assume constant loss susceptibility over time, a doubling of the capital stock at risk results in a doubling of the losses. We assume that the capital stock at risk in 2050 is 297% higher than in 2005 (in 2005 prices). The frequency distribution F of the random variable X_k shifts accordingly. The new distribution of the storm loss F_{se} affected solely by the increase in material assets at risk is derived from:

$$F_{se} = F \times (1 + se) \tag{6.3}$$

The parameter se stands for the socio-economic change (change in the capital stock) and is 2.97. Because of the assumed linear increase in losses relative to the level of the capital stock, the frequency distribution F shifts to the new distribution F_{se} by a factor of 3.97. This adjusted frequency distribution is the basis for the simulation of the average annual loss in 2050, assuming no changes in storm intensity.

The same assumptions on cc and se are used for the simulation of the total average annual loss resulting from higher wind speeds and higher capital stock at risk. The shift in the frequency distribution F_{ccse} of the random variable X_k reflecting the overall effect is derived from:

$$F_{ccse} = F \times \left((1 + se) + (1 + cc)^3 - 1\right) \tag{6.4}$$

The new frequency distribution F_{ccse} for the random variable X_k (loss per storm) is obtained by shifting the frequency distribution F by a factor of 4.063. It is the basis for the simulation of the average annual loss in 2050 assuming a change in storm intensities and a higher level of capital stock.

6.4.5 Results of the simulations for the year 2050

Table 6.3 summarises the results of the three simulations performed on the influence of the change in risk situation, the change in the capital stock at risk, and the effect resulting from both changes. The same random variables are used in all three Monte Carlo simulations.

The change in the assumed risk situation (increase in wind speeds, constant frequency) resulting from anthropogenic climate change results in roughly an 11% higher average annual loss, or in additional losses of approx. 1 billion US$ (in 2005 prices). This is much less than would be expected from the increase in capital stock in the storm-prone regions. Because of the increase in capital stock, the average annual loss rises from 9.1 billion US$ in 2005 to 37.3 billion US$ in 2050 (in 2005 prices). This represents an increase of 308%. The average loss from North Atlantic cyclones in the year 2050, both from anthropogenic climate change and from an increase in capital stock, is 38.1 billion US$ (in 2005 prices). This represents an increase of 317% on 2005.

Table 6.3: Average annual loss and additional loss in the different scenarios for 2050.

	Annual loss in million US$ (US$ 2005) and loss increase (%)						
	1950–2005	2050cc		2050se		2050ccse	
Historical storms 1950–2005	9,980.3	-	-	-	-	-	-
Simulation	9,135.8	10,114.1	+10.7%	37,305.4	+308.3%	38,121.5	+317.3%

The scenarios are based on the following assumptions
2050cc wind speed +3%; increase in wealth +0%; elasticity of losses to wind speed 3
2050se wind speed +0%; increase in wealth +297%; elasticity 3
2050ccse wind speed+3%; increase in wealth +297%; elasticity 3

6.4.6 Assumptions and simulation results for the year 2015

The assumptions and results described above describe the longer-term perspective of this study, namely the effects of anthropogenic climate change, and the future socio-economic changes up to the middle of this century. However, it is also interesting, particularly for the insurance of natural catastrophes, to look at the near future. We therefore performed the simulations for a medium-term perspective as well. We simulated the loss that would result in the year 2015 with the anticipated risk situation and the increase in capital stock at risk.

The assumption remains that there will be no increase in the frequency of tropical cyclones. It is also assumed for the year 2015 that there is an increase in the wind speeds of the storms. The starting basis is once again a 6% increase in wind speeds by the end of the 21st century compared to the end of the 20th century (cf. Bengtsson et al., 2007). Assuming a linear increase, this results in 0.9 per cent higher wind speeds for 2015. The assumption for loss elasticity to wind speed is once again 3. With the assumed annual increase in the capital stock of 3.1%, the latter will be 36% higher in 2015 than in 2005 (in 2005 prices).

Table 6.4 summarises the results of the simulations for the year 2015. An average annual loss that is roughly 4% higher can be expected in 2015, as result from the change in risk situation. It increases by 32

per cent because of the increase in capital stock in the regions affected by the storms. Together, both effects result in a loss of increase of 35%.

Table 6.4: Average annual loss and additional loss in the different scenarios for 2015.

	Annual loss in million US$ (US$ 2005) and loss increase (%)						
	1950–2005	2015cc		2015se		2015ccse	
Historical storms 1950–2005	9,980.3	-	-	-	-	-	-
Simulation	9,461.9	9,870.7	+4.3%	12,516.7	+32.3%	12,803.0	+35.3%

The simulations for 2015 and 2050 were carried out independently of one another. Correspondingly, other random statistics were incorporated that explain the slight deviation between the simulations for the average annual loss for 1950–2005.

The scenarios were based on the following assumptions
2015cc wind speed+0.9%; increase in wealth +0%; elasticity of losses to wind speed 3
2015se wind speed+0.0%; increase in wealth +36%; elasticity 3
2015ccse wind speed+0.9%; increase in wealth +36%; elasticity 3

6.5 Discussion

The results of the simulations diverge significantly from the additional costs calculated by Nordhaus (2006), Hallegatte (2007a) and Pielke Jr. (2007a) resulting from anthropogenic climate change and from socio-economic trends. When applied to the year 2050, these studies give an average annual loss increase from anthropogenic climate change of 52% (Nordhaus, 2006), 27% (Hallegatte, 2007a) and 64% (Pielke Jr., 2007a).[51] Pielke Jr. (2007a) predicts a loss increase of 360% in 2050 from the combined effects of climate change and socio-economic trends. The deviations between these results and the results in our simulations, and also the deviations between one study and another can be explained by the uncertainties relating to the change in risk situation, the development in capital stock at risk (which only Pielke Jr., 2007a makes allowance for) and the loss elasticity to wind change. The following section therefore presents the results of a sensitivity analysis that was carried out using the assumptions in the three studies mentioned. We will look firstly at the results for the effect of higher wind speeds.

Nordhaus (2006) and Pielke Jr. (2007a) assume that the frequency of cyclones does not change. Hallegatte (2007a) applies an increase in the frequency of landfalls, as a result of storms he generated synthetically, using a physical storm model. We do not make any allowance for this in the sensitivity analysis.

Nordhaus (2006) assumes an 8.7% intensification of storms by the end of the century as a result of anthropogenic climate change. This intensification is based on the 2.5°C ocean warming that he anticipates, and on the scenario posited by Knutson and Tuleya (2004), whereby each degree of warming of the sea surface temperature leads to a 3.5% increase in wind speeds. Hallegatte (2007a) initially uses a physical storm model for synthetic storms under the climate conditions he expects to prevail at the end of the 21st century. In this context, he anticipates a 10% increase in the potential intensity of storms (based on Emanuel, 2005b). For the dataset of synthetic storms, he calculates an increase in wind speeds of 13%. Based on an expert survey, Pielke Jr. (2007a) assumes an 18% intensification of storms by 2050 (or +36% by 2100). As regards the increase in wind speeds by the end of the 21st century, therefore, the assumptions in the three studies range from 8.7% to 36%. In this context, we have assumed a lower figure of 6% for the end of the century. Pielke Jr. (2007a) and Hallegatte (2007a) assume three as the elasticity of loss to wind speed, just as we have done, while Nordhaus (2006) assumes a much higher elasticity of 8.

If we apply the assumptions from Nordhaus (2006) in our model, we obtain a 107% higher average annual loss at the end of the 21st century. This closely matches the figure of 104% determined by Nordhaus. Based on the assumptions from Hallegatte (2007a), our model produces an increase in the average annual loss of 49%. Hallegatte's own figure is 54%. The fact that we might slightly underestimate the loss increase can be explained by the fact that Hallegatte additionally allows for a greater frequency of cyclones making landfall. If the assumptions from Pielke Jr. (2007a) on storm intensification are applied, our model produces a 66% greater annual loss. Pielke Jr. himself gives a figure of 64%. Using the assumptions from the three studies, we can reproduce their results. This illustrates that the deviations between the studies and the results of our simulations, and among the studies themselves can basically be explained by the assumptions made. Differences in method do not play a relevant role. Additional studies would therefore be extremely welcome if they help to reduce uncertainties on the change in frequency and intensity of futures storms, and regarding loss elasticity to wind speed. Table 6.5 compares the assumptions and the results of the studies, as well as the average annul loss increases we calculated based on their assumptions.

Only Pielke Jr. (2007a) investigated the impact of an increase in material assets in the affected regions. For the scenario with the slow trend in population and wealth, he assumes that the population and level of wealth in the storm-prone regions will increase by a factor of 2.8 by 2050 compared to 2006. This increase corresponds to an annual socio-economic growth of 2.5%. This value is under the 3.5% that average estimates globally assume (cf. Pielke Jr., 2007a). With no change assumed for vulnerability, losses in Pielke Jr. increase in linear fashion along with the material assets at risk. With a 180% increase in wealth, this leads to a 180% increase in losses. The result of our model's 10,000-year simulation, assuming a 180% increase in wealth by 2050, is a 185% higher average annual loss (see Table 6.6).

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[51] The calculations in Nordhaus (2006) and Hallegatte (2007a) relate to the end of the 21st century. Here, these have been linearly extrapolated for the year 2050.

According to Pielke Jr. (2007a), there is a 360% increase in the annual loss for the effects from higher wind speeds and from the increase in level of wealth (exposure). We can also verify this result using our model. We arrived at an increase of 368% (see Table 6.6).

Table 6.5: Change in average annual loss as a result of global warming – simulations applying the assumptions from current studies.

	Nordhaus (2006) (relating to the end of the 21st century)	**Hallegatte (2007a)** (relating to the end of the 21st century)	**Pielke Jr. (2007a)** (relating to 2050)
Assumed change in frequency	constant	increase in landfalls	constant
Assumed change in wind speed	+8.7%	+13%	+18%
Assumed loss elasticity to wind speed *el*; loss function $d = \alpha \times wind\ speed^{el}$	*el* = 8	*el* = 3	*el* = 3
Change in loss (result of the study)	+104%	+54%	+64%
Change in loss (simulation result based on study assumptions)	+107%	+49%	+66%

Table 6.6: Change in average annual loss in 2050 as a result of socio-economic changes and of the overall effect from the change in socio-economic effects and wind speed - simulations applying the assumptions in Pielke Jr. (2007a).

	Pielke Jr. (2007a) – change in wealth	**Pielke Jr. (2007a) – change in wealth and wind speed**
Assumed change in frequency	-	constant
Assumed change in wind speed	-	+18%
Assumed loss elasticity to wind speed *el*; loss function $d = \alpha \times wind\ speed^{el}$	-	*el* = 3
Assumed increase in wealth	+180%	+180%
Assumed combined effect from changes in wealth and wind speed	-	+116%
Change in loss (result of the study)	+180%	+360%
Change in loss (simulation result, based on the assumptions from Pielke Jr., 2007a)	+185%	+367%

As in all the other studies quoted, our simulations have only incorporated the effects from anthropogenic climate change on the intensity of storms. We have assumed that global warming leads to a linear increase in storm activity. In reality, however, the natural fluctuation in sea surface temperature in the North Atlantic, the so-called Atlantic Multidecadal Oscillation (AMO), has a much greater influence on storm activity. Depending on the deviation from the multi-year mean, one talk of a "cold phase" or a "warm phase". These phases generally last several decades. Warmer phases trigger higher tropical cyclone activity.[52] Since 1995, the North Atlantic has been in a warm phase again (cf. Goldenberg et al., 2001) whose end cannot be precisely predicted. If the years we simulated, 2015 and 2050, lie within a cold phase, the level of storm activity will be well below that of today. The assumed intensification of storms as a result of global warming would then be overcompensated for by a natural decline in storm frequency and storm intensity. The annual losses that actually occur in 2015 and 2050 should in this case be below those simulated in this study.

Natural climate variation may even have an effect on losses only, since anthropogenic climate change produces no change in storm activity. Using the approach taken by Vecchi et al. (2008), the factors underlying Atlantic storm activity cancel one another out. This is why storm activity remains unchanged despite global warming.

6.6 Simulation of the average annual loss for individual storm categories

The average annual loss only gives us a restricted picture of how the loss situation might develop in future. For example, the average annual loss between 1950 and 2005 varies by 157 billion US$ (in 2005 prices) (see Table 6.1). This is the result of high variability, both in terms of the number of storms, and of the single event losses, caused among other things, by the natural variation in climate. We have therefore supplemented our simulation of the additional loss increase in 2050 for the categories of light, weak to moderate, and strong to devastating storms. We describe a storm with wind speeds <33 m/s as a light storm. These are storms that do not reach hurricane strength. We categorise storms in categories H1 and H2 of the Saffir-Simpson scale, with wind speeds of 33 m/s up to 50 m/s, as weak to moderate storms. Storms with winds speeds >50 m/s, such as storms in categories H3–H5, are classed as strong to devastating storms. Figure 6.1 shows the distribution to the three categories of the 131 storm events recorded for the years 1950–2005.

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[52] The terms "cold phase" and "warm phase" are strongly linked to the idea of natural fluctuations in climate, as described by the AMO (cf. inter alia Goldenberg et al., 2001, Kossin and Vimont, 2007, Zhang and Delworth, 2006). However, there are also climatologists who see no influence of natural variability in climate. According to this opinion, the terms "cold phase" and "warm phase" make no sense (cf. Mann and Emanuel, 2006). The phenomenon of cooler SSTs in the past ("cold phase") does not result from a natural fluctuation in climate, but from anthropogenic aerosol emissions into the atmosphere that result in temporary cooling in the atmosphere and in the sea.

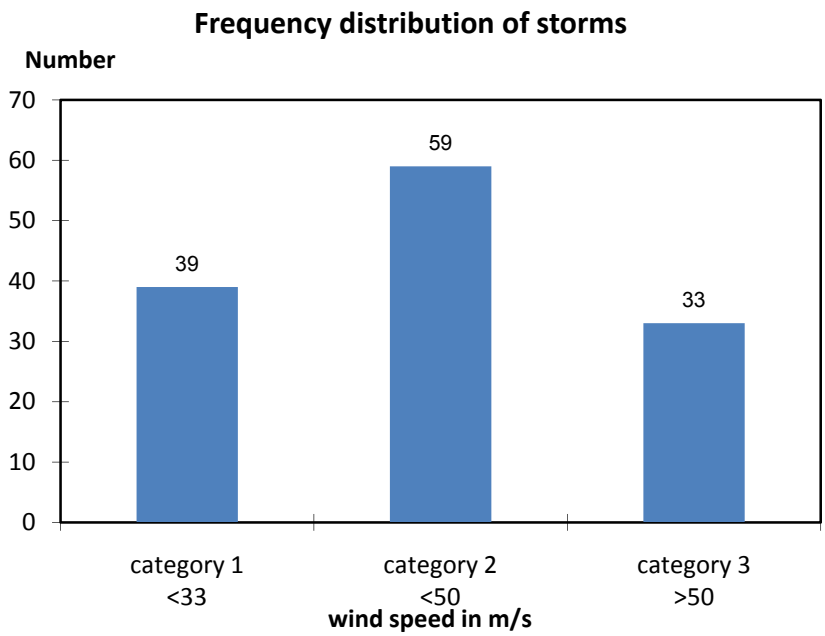

Figure 6.1: Number of storms 1950–2005 in the three storm categories.

Table 6.7 gives the mean empirical annual loss per storm category for the years 1950–2005. It also shows the average annual losses from 10,000 simulated years, in each case with an assumed 3% increase in wind speeds, and a 297% increase in capital stock at risk, as well as for the effect of the two factors combined.

Table 6.7: Average annual number, loss and additional loss in the different scenarios for 2050 according to storm category.

	Cate-gory	**Num ber**	**Annual loss in million US$ (US$ 2005) and loss increase (%)**						
			1950–2005	2050cc		2050se		2050ccse	
Histor. storms 1950–2005	I	0.7	939.6	-		-		-	
	II	1.1	1,657.0	-		-		-	
	III	0.6	7,383.7	-		-		-	
Simulations	I	0.7	779.9	854.7	+9.6%	3,235.9	+314.9%	3,444.8	+341.7%
	II	1.0	1,455.7	1,593.5	+9.5%	5,657.5	+288.6%	5,934.2	+307.7%
	III	0.6	6,912.3	7,465.5	+8.0%	21,223.8	+207.0%	27,541.7	+298.4%

Classification of storms according to wind speed: category I <33 m/s, category II 33 m/s to 50 m/s and category III >50 m/s.

6.7 Summary

Ever since the two extreme hurricane years of 2004 and 2005, there has been a discussion in the media and the science community about the level of losses from tropical cyclones that economies will have to face in the future. A particular focus of the debate is on the influence of anthropogenic climate change. However, this is just one of the factors that will more likely than not contribute to an increase in losses. The principal factor will be the increase in capital stock affected by such storms. This is increasing because more and more people are settling in storm-prone regions, with ever-greater concentrations of material assets.

In this chapter we have examined the increase in the average annual loss from Atlantic cyclones in the USA in the years 2015 and 2050, resulting from a climate-induced change in the risk situation (frequency and intensity of the storms) and by the increase in material assets at risk. A stochastic model was used for the analysis. The model simulates the storm frequency and the loss per storm event for a large number of years and then calculates an average annual loss from this. This model was adjusted for the anticipated changes in risk situation, vulnerability and material assets at risk. The results show that the increase in the average annual loss is principally caused by the increase in capital stock. Nevertheless, anthropogenic climate change will also lead to noticeable loss increases. In our study, the latter is 11% for the year 2050. That's an increase lower than the results from other studies. Based on the results from Nordhaus (2006) and Stern et al. (2006), losses could increase by 50% by 2050. According to Pielke Jr. (2007a), the figure could be as high as 64%.

From a medium-term perspective (2015), losses from anthropogenic climate change will still increase by 4%. They will rise by an additional 32% due to the increasing amount and the average value of material assets in the regions affected by the storms. In evaluating the changes resulting from climate change and socio-economic trends, it should be remembered that the rise in losses resulting from socio-economic changes is offset by an increase in wealth in the form of the higher capital stock. In contrast, the increase in losses caused by climate change is not offset by any other increase. This loss increase leads to a reduction in wealth.

From the perspective of the insurance industry, which must assume the transfer of risk from weather extremes, the results should be assessed as follows. The increase in losses resulting from the rise in the capital stock basically poses no problems for insurers since the premium will rise according to the increase in capital stock or the sum insured. The increase in wind speed will change the risk situation. Besides the changes due to natural climate variability, this should be taken into account in premium calculation. As well as adjusting premiums, insurers could also respond to the changing risk situation from natural climate variability and anthropogenic climate change by adjusting deductibles. With the deductible, the insured party bears the loss itself up to an agreed amount. The insurer or reinsurer is only involved when this limit is exceeded. If deductibles are not adjusted, they will be exceeded more quickly in future due to the anticipated higher wind speeds and the higher resulting loss.

Table 6.8: Overview of studies to estimate future storm losses in the USA resulting from global warming.

Study	Loss function	Assumed change in intensity	Assumed change in frequency	Result
Cline (1992)	Increase in intensity produces a linear increase in losses	Increase of 40–50% with 2.3–4.8°C warming	-	Average loss increases by 50%
Fankhauser (1995)	Increase in intensity triggers a 1.5 increase in losses	Increase of 28% with warming of 2.5°C	-	Average loss (global) increases by 42%
Tol (1995)	Connection is in the quadratic form $f(X) = aX + bX^2$	Increase of 40–50% with warming of 2.5°C	constant	Increase in losses of 300 million US$ (1988 values)
Nordhaus (2006)[a]	$d = \alpha \times wind\ speed^8$	Increase of maximum wind speeds of 8.7% with warming of 2.5°C	constant	Average loss increases by 104%
Stern et al. (2006)	$d = \alpha \times wind\ speed^3$	Increase of 6% with warming of 3°C	-	Average loss increases by 100%
Hallegatte (2007)[b]	Physical storm model to create synthetic storms; loss function in the form $d = \alpha \times (s) \times wind\ speed^3$	Increase of 10% under the expected climate conditions at the end of the 21st century	no change in absolute number	Increase in landfalls and maximum wind speed (+13%) Average loss increases by 54%
Pielke Jr. (2007a)	$d = \alpha \times wind\ speed^3$ (further scenarios with elasticity of 6 and 9)	Increase of 18% by 2050	constant	Increase in loss of 64%[c]

Notes
[a] Losses adjusted for economic development using GDP.
[b] Losses adjusted for population and wealth trends, *s* for vulnerability index.
[c] Additional loss increase of 116% from the combined effect of increase in intensity and socio-economic trend.

7 Summary, conclusions and outlook

Economic losses caused by weather-related natural catastrophes have increased over the last decades. Tropical cyclones in the USA account for a major portion of these losses. The underlying causes of the loss increase are known. Essentially, they can be divided into climate-related and socio-economic factors. The climate-related factors comprise changes in the frequency and intensity of weather extremes. The socio-economic factors include changes in vulnerability and in the level of assets at risk from the natural hazard (exposure). As well as these two groups of factors, the statistics are influenced by changes in access to, and in the assessment of, natural catastrophe losses.

Socio-economic and climate-related trends will lead to further loss increases in the future (cf. IPCC, 2007b). At the present time, the socio-economic factors are the principal drivers of the observed loss increase (cf. IPCC, 2007b) and are likely to remain so in the future. The extent to which anthropogenic climate change has already influenced the trend in losses, or will influence it in the future, has yet to be clarified. For this, the portion of the loss increase that is due to socio-economic and climate-related factors still needs to be reliably quantified (see also Höppe and Pielke Jr., 2006). This task is considered difficult, particularly because of the available data quality, the stochastic nature of weather extremes, and the parallel influence of both groups of factors (cf. Diaz and Pulwarty, 1997, Höppe and Pielke Jr., 2006, Reinhart, 2004).

The insurance industry has a special interest in determining what portion of the overall trend is due to climate-related or socio-economic losses. It is one of the first sectors to be affected by a change in the risk situation as a result of global warming. But a change in the risk situation is of significance for more people than just insurance companies, since the latter pass on the effects of such a change to the general public, in the form of premium adjustments and risk selection (cf. Mills, 2005).

The present doctoral thesis provides additional components to help reduce the uncertainties surrounding the role of socio-economic and climate-related factors in the loss trend. It focuses on providing answers to two different questions:

- Is it possible to quantify more precisely the influence that climate change (both anthropogenic and natural) has on the increase in losses already?
- What losses may be expected in the medium and long term, if we make allowance for both climate-related and socio-economic trends in the future?

By way of example, these issues are examined in three studies on losses in the USA from North Atlantic tropical cyclones.

The first study starts by isolating the socio-economic effects contained in the loss data and then subjects this data to a trend analysis (see also Schmidt, Kemfert, Höppe, 2009). Any remaining trend in the adjusted loss data could no longer be explained as due to socio-economic developments, but would instead point to a change in the risk situation that is very probably the result of climate change. The study there-

fore adjusts the losses from 131 storms in the years 1950–2005 to the socio-economic level of 2005. The level of the loss for each storm is thus given as if the storm had occurred in the year 2005. The adjustment is based on a new approach whereby the loss data are adjusted for the changes in the capital stock at risk. The latter is obtained from the value of all housing units in the US counties affected by the storm. The "Normalized Hurricane Damages" approach presented in Pielke Jr. and Landsea (1998) is currently the leading method of adjusting loss data for socio-economic effects (see also Pielke Jr. et al., 2008). There are two essential differences between the approach presented in this thesis and that of Pielke Jr. and Landsea. Firstly, the use of capital stock at risk (determined from the number of housing units and mean home value) instead of wealth at risk (determined from population and per capita wealth). Secondly, the application of regional figures for mean home value instead of the national average for per capita wealth. If the results are compared, it can be seen that all factors that normalise losses resulting from wealth at risk are higher than the factors used to adjust losses based on capital stock at risk. The further back in time the losses lie, the greater the disparity. However, no differences in the remaining trend were identified for the relatively short time series 1971–2005. A remaining positive trend that is statistically significant is found for this period. The losses increase on average by 4% per year.[53] However, the remaining positive trend does not confirm a trend in the storm losses that can be directly related to global warming from anthropogenic greenhouse gas emissions. At the very least, however, the trend is the result of natural climate variability. The sample period 1971–2005 begins at a phase of low storm activity in the North Atlantic and ends in the current phase of high activity. The change in the activity level is the result of natural climate variability in the North Atlantic. The IPCC states that it is more likely than not that human activities play a role in this increase in storm activity too (cf. IPCC, 2007a). It is therefore more likely than not that a portion of the loss increase stems from anthropogenic climate change (cf. Schmidt, Kemfert, Höppe, 2009).

The second study examines how sensitive storm losses are to changes in socio-economic and climate-related factors, and looks at how these factors developed in the period 1950–2005. Based on this, conclusions are then drawn on the shares the factors have in the overall trend (see also Schmidt, Kemfert, Höppe, 2010). For the purpose of the analysis, the loss is depicted as a function derived from the value of the material assets (capital stock) at risk and the intensity (in this instance wind speed) with which the storm impacts these assets. In most studies, the loss function is only expressed as a function of the storm intensity. To remove the influence of changes in capital stock over time, the loss data are therefore adjusted for the socio-economic influences from the increase in wealth (as in Nordhaus, 2006). A new feature of the approach used in the thesis is the direct inclusion of the capital stock variable in the loss function. The socio-economic influences are therefore expressly included in the analysis, instead of being removed from it. The loss function used takes the form of a Cobb-Douglas production function. Using an econometric estimate, we can therefore determine the elasticity of the loss function. The elasticity findings show that losses are much more responsive to a change in storm intensity than to a change in capital

[53]The same results are obtained if we look at the Pielke Jr. et al. (2008) dataset of normalised losses over the same period (Roger Pielke Jr., personal communication).

stock. It is already known that losses rise sharply in response to a marginal increase in storm intensity. However, estimates of this elasticity in the literature vary considerably. One innovation in this thesis is that loss elasticity is also estimated relative to changes in capital stock. The fact that the result is lower than one could be interpreted to mean that new housing units that increase the capital stock are of better design and are more resilient to storms. The vulnerability of buildings in the regions of the USA affected by storms is therefore decreasing over time (as also concluded by Jain et al., 2005). A change in the capital stock at risk therefore produces a smaller change in the loss than a change in storm intensity. Over the period 1950–2005, however, there has been a much greater change in capital stock than in storm intensity. Based on these trends and the elasticity factors, we find that the increase in losses between 1950 and 2005 was approximately three times higher for socio-economic changes (+190%) than for climate-related changes (+75%). The extent to which the climate-related changes are the result of natural climate variability, or of anthropogenic climate change, must remain open. The influence of natural climate variability can be removed if only "warm phases" (phases with warmer sea surface temperatures and thus greater storm activity) are compared with one another. The above-mentioned climate-related change is based on the increase in the average level of intensity in the last "warm phase" in relation to the average in the current "warm phase", which has not ended yet. At 27%, this increase is well above the long-term average. Since 1870, the storm intensity between one "warm phase" and another has increased by between 0.4% and 5%. If this lower increase is taken as a basis for the period 1950–2005, losses have "only" risen by between 1.4% and 14%. Despite the many uncertainties, this is at least an indication that the loss increase is also due to global warming (cf. Schmidt, Kemfert, Höppe, 2010).

The procedure in the first study only allows indirect conclusions to be drawn about the influence of the climatic changes. Losses are only adjusted for the change in wealth, so that other factors influencing the losses remain in the data. The climate-related influences are only one factor among many. The second study uses no data that have been adjusted for changes in wealth. The influence of the socio-economic factors, instead of being removed, has been expressly included. The second study also has certain shortcomings that must be taken into account when interpreting the results. However, if the two approaches are compared, the one used in the second study is better suited to explaining what portion of the overall trend is due to socio-economic and climate-related losses.

The third study simulates the change in the average annual loss in the future. It carries out simulations for the years 2015 and 2050, but not just for the additional losses expected from global warming, and thus from an intensification of tropical storms, as most of other studies on this topic. It also simulates the additional losses that will result from socio-economic developments in the future (see also Schmidt, Kemfert, Faust, 2009). The simulation of the total losses allows us to estimate the overall burden that will be faced by state and private forms of risk transfer to insure the natural hazard "tropical cyclone" in the USA. A stochastic model, whose components are the number of storms and the loss for each storm, is used for the simulation of the annual loss. An average annual loss is then determined from simulated 10,000 annual losses using a Monte Carlo simulation. The simulations are based on assumptions about the trend in capital stock in the areas at risk and on increasing storm intensity as a result of global warming. The results show that the increase in wealth will remain the key driver of losses in future. In the year 2050, losses will be 300% higher than in the base year of 2005. But anthropogenic climate change will also lead to

noticeable loss increases. Losses in the year 2050 will be 11% higher because of an intensification of the storms. When interpreting the results of the simulations, it must be remembered that even though socio-economic factors lead to a much higher loss increase, they are not responsible for any actual loss of wealth. The higher losses are compensated for by a higher amount of capital stock, in this case understood as an approximation of the level of wealth. In contrast, there is no increase in wealth elsewhere to compensate for the increase in losses from the intensification of the storms due to anthropogenic climate change. This loss increase therefore results in a real loss of wealth (cf. Schmidt, Kemfert, Faust, 2009). The result of an 11% increase in costs is low in comparison with three other current papers (Hallegatte, 2007a, Nordhaus, 2006, Pielke Jr., 2007a). For 2050, these studies determine an increase in losses of between 27% and 64%.[54] The uncertainties relating to the additional costs from anthropogenic climate change basically stem from the assumptions made about the change in frequency and intensity of the storms, and the elasticity of losses to storm intensity. However, it is immaterial which simulation method used. The three papers use different methods and assumptions to simulate the additional costs of climate change. It was possible to verify the results using the method developed in the present thesis and the assumptions made in the respective papers.

So the three studies in the thesis provide answers to the questions posed at the start. But how reliable should we consider these answers to be? There are various uncertainties underlying the results, as the discussion in this chapter and also in the three different studies shows. All quantitative results should therefore be seen as an indication, rather than a confirmation, of the influence of anthropogenic climate change. According to Höppe and Pielke Jr. (2006), it will be some time before the relationship between the trends for storm losses and anthropogenic greenhouse gas emissions can be clarified in a satisfactory way. This view is confirmed by the thesis. Despite its limitations, it shows that, more likely than not, anthropogenic climate change is already influencing and will continue to influence losses from cyclones.

What conclusions can now be drawn from the results? It can be stated that socio-economic factors have been the principal drivers of the loss increase up to now, and are likely to remain so in the future. Assuming the current loss trends continue, Bouwer et al. (2007) perceive the risk of global catastrophe losses developing to the point where they exceed the trend in economic growth. They therefore call for a reduction in the catastrophe risk to be given a central role as part of efforts to adjust to natural climate variability and anthropogenic climate change.

Even if adjustment measures represent the principal lever to reduce weather-related natural catastrophe losses, mitigation efforts of greenhouse gases should still be seen as both sensible and necessary. If it remained unchecked, anthropogenic climate change would probably cause significant losses. We should also not overlook the fact that mitigation efforts would not just have a positive effect on losses from

[54] The calculations in Nordhaus (2006) and Hallegatte (2007a) relate to the end of the 21st century. Here, these have been linearly extrapolated for the year 2050.

weather extremes, but would also influence the other costs generated by global warming. Take, for example, the impact of a rise in sea levels, or the adjustment costs in the agricultural sector.[55] This thesis conclude that the avoidance of greenhouse gas emissions should therefore play a central role in reducing the catastrophe risk too.

If we look at the results of the doctoral thesis from an insurance industry perspective, we see that a rise in losses due to socio-economic developments generally poses no problem for insurers. There is a linear increase in the insurance premium in tandem with the sum insured, in other words the capital stock at risk. The loss ratio of premium income to paid losses remains constant despite the higher losses. However, if the losses increase due to a change in the risk situation for climate-related factors, the loss ratio also rises. To prevent this, the premium calculation needs to be adjusted. Faust (2006a) pointed out that long-term changes due to climate change have so far not been factored in to loss distributions for the premium calculation.

This thesis has concentrated on one region, the eastern USA, and on one natural hazard, tropical cyclones. In principle, the approaches presented can also be applied to other regions and natural hazards. This is to be welcomed, since with few exceptions, the literature up to now has focused on losses from tropical cyclones in the USA. It would be interesting to see further studies on a possible climate signal in the loss data, and also a simulation on additional losses due to anthropogenic climate change. Up to now, either no allowance or insufficient allowance has been made for the additional costs from weather extremes in economic models on the costs of anthropogenic climate change. Extending the analysis carried out in this thesis to other regions and natural hazards would enable us to form a fuller picture of the additional costs that may be expected from global warming.

One difficulty associated with adapting the approach to other regions relates to the data required. Data on regional capital stocks are required that would not be available for most regions. One alternative would be to use statistics on population and gross domestic product (GDP). However, data on both of these should be available at regional level, in other words for the regions at risk from natural hazards. A further possibility to determine regional capital stocks would be to use the information on sums insured in the region under investigation. To do this, however access would need to be obtained to the databases of risk modelling companies and insurance companies.

There has been little analysis so far of the overall future costs resulting from socio-economic and climate-related trends. Apart from the USA, which today has a high concentration of assets in regions at risk from storms, the loss potential will also increase in other exposed regions, for example in coastal regions in China, where there has been an dramatic increase in capital stock. At the same time, the Chinese coast is also at high risk from tropical cyclones. But China is just one example. The population and the level of

[55] An increase in sea levels also produces an additional increase in the risk from storm damage. For the USA, Nordhaus (2006) finds that a rise of one centimeter in sea level corresponds to an increase of 1% in the capital stock at risk.

wealth are increasing in many other developing and newly industrialising countries, accompanied by an increasing concentration in conurbations. In many cases, this is happening in regions at risk from natural hazards. We can therefore assume, with a high degree of probability, that both the number and the amount of losses in future from weather-related natural catastrophes will increase, based solely on socio-economic trends. On top of this, changes in extreme weather events must be expected as a result of anthropogenic climate change. Such changes will affect the frequency, regional occurrence and intensity of such events, and must be expected to further exacerbate the situation. In view of the sensational nature of the expected trends, there has been surprisingly little quantitative analysis of the topic of overall future costs from weather extremes. It would be practical to simulate future overall costs for other regions and also for other natural hazards. Insurers are only one group who would be interested in this approach as a way of identifying future "hot spots" for natural catastrophes. Analyses of this kind will also make an important contribution for cost-benefit analyses on catastrophe prevention measures.

Appendix

Table A 1: Overview of variables and parameters.

Designation	Explanation
μ	Expected value of the number of storms
cc	Parameter change in wind speed as a result of global warming
$cs_j(2005)$	Index for the value of all material assets (capital stock) in 2005 in the US counties affected by storm j
$cs_j(y)$	Index for the inflation-adjusted value of all material assets (capital stock) in occurrence year y in the US counties affected by storm j
D	Adjusted annual loss
el	Loss elasticity relative to changes in capital stock index or wind speed
F	Frequency distribution of the random variable X_k (loss from storm k)
F_{cc}	Frequency distribution of the random variable X_k because of anthropogenic climate change
F_{ccse}	Frequency distribution of the random variable X_k because of anthropogenic climate change and higher capital stock
F_{se}	Frequency distribution of the random variable X_k because of higher capital stock
j	Index for storm
k	Index for storm (with adjusted loss)
m	Number of years in period 1950–2005
$N(t)$	Random variable for the number of storms in the interval $[0;t]$
n_y	Number of storms in the year y within a period of m years
s	Index for affected US state
se	Parameter change in capital stock as a result of socio-economic development
t	Time index; here always = 1 (one year)
w	Average growth rate in annual losses
ws_j	Wind speed of storm j at landfall
$x_j(y)$	Inflation-adjusted loss from storm j at the level of wealth in year of occurrence y
X_k	Random variable loss from storm k

$x_k(y)$	Loss from storm k in the year y in the prices and at the level of wealth in 2005 (adjusted loss of storm j)
y	Index for year
α	Constant
β	Trend parameter

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