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DISCLAIMER

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ABSTRACT

This report summarizes current research on how climate change is likely to influence future losses from extreme weather events. We consider six types of weather-related extreme events: tropical cyclones, extratropical cyclones, inland floods, landslides and avalanches, wildfires, and small-scale storms. For each type of event, we synthesize existing research related to three topics. First, we examine research that estimates historical average losses from each type of extreme weather. We find that while there are relatively good data on costs of destroyed infrastructure, there is considerable disagreement in the literature about the longer-term macroeconomic effects of disasters. Second, we summarize evidence on the relationship between socioeconomic growth and storm losses. Our review suggests that increases in GDP and population lead to higher losses from disasters, but that disaster mortality is lower in more developed countries. Finally, we review studies of how climate change will affect future losses from extreme weather. Many studies predict increases in losses under climate change, but the science remains uncertain and some projections suggest that certain types of extreme weather losses may decrease. Overall, based on a reduced-form model that draws together parameter estimates from each of these three strands of literature, we estimate that moderate climate change will cause average extreme weather damages to increase by tens of billions of dollars per year. However, the confidence intervals surrounding our estimates are very wide, reflecting substantial underlying uncertainties.

JEL Classification: Q54

Keywords: Climate change, impacts, extreme weather, tropical cyclones, extratropical cyclones, floods

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1 Introduction

Events related to extreme weather cause substantial economic damages worldwide. Over the last thirty years, worldwide direct reported losses have averaged $28 billion from tropical cyclones, $2 billion from extratropical cyclones, $10 billion from inland floods, $0.3 billion from landslides and avalanches, $2 billion from wildfires, and $7 billion from small-scale storm-related phenomena (Guha-Sapir, Below, and Hoyois, 2015). Recent research suggests that climate change will influence the frequency, intensity, and geographic distribution of these types of extreme events (Bender et al 2010; Knutson et al 2010; IPCC, 2012; Cai et al, 2015)—leading to corresponding changes in future economic impacts (Karremann et al, 2014; Susnik, 2014; Neumann et al, 2014).

However, despite a recent surge in scientific and economic literature on this topic, the representation of extreme weather damages in integrated assessment models (IAMs) of climate change remains relatively basic. Two of the leading IAMs—the DICE model (Nordhaus, 2013) and the PAGE model (Hope, 2006)—assert that their aggregate damage functions include extreme weather losses, but do not attempt to model losses separately for this category. The FUND model does have separate modules that cover tropical and extratropical cyclone losses (Narita, Tol, and Anthoff, 2009; Narita, Tol, and Anthoff, 2010), but the parameters are based on older research, and the model excludes other important categories of extreme events, such as inland flooding.

As a step towards improving the way that IAMs represent extreme weather, this report reviews the growing literature on climate change and extreme weather losses. Because there are many different ways to define extreme events, we limit our focus to categories of weather-related events that cause direct damage to physical infrastructure over a short time-frame. This criterion includes the following categories of events: tropical cyclones, extratropical cyclones, heavy precipitation, inland flooding, landslides and avalanches, wildfires, and small-scale storm-related phenomena (hail, tornadoes, thunderstorms). It excludes climate-related events that take place over longer time scales, such as droughts, monsoons, El Nino and other oscillations, and extreme sea levels. For each type of disaster, we consider three topics.

First, we review research that estimates historical average losses from each type of extreme weather event. Most previous modelling efforts have used data on reported losses taken from global disaster databases maintained by reinsurers or by academic organizations. Although these databases are the only reasonably comprehensive source of information about the costs of destroyed infrastructure, they omit many important categories of costs, particularly longer term impacts. Thus, to supplement this data, we also review recent empirical research on the macroeconomic costs of extreme weather events. We find that there is considerable disagreement in the literature about the effects of disasters on GDP, with a few studies suggesting positive growth effects from rebuilding outdated infrastructure, but other studies finding very large negative long-term growth effects.

Second, we summarize recent research on the relationship between socioeconomic growth and storm losses. A large number of studies have measured long-term trends in losses per capita or per unit of GDP. However, these studies reveal little about the causal effect of socioeconomic change on losses. In our review of studies that use a regression-based approach, we find support for the hypothesis that increases in GDP and population lead to higher losses from disasters. However, the literature also suggests that disaster mortality declines as countries become more developed.

Third, we review studies of how climate change will affect future losses from extreme weather. Many studies predict increases in losses under climate change, but the science remains uncertain and some projections suggest that certain types of extreme weather losses may decrease.

Based on our review of these three topics, we develop reduced-form damage functions for each of the six categories of extreme weather events. The models use simple, IAM-compatible functional forms. We parameterize the models by developing probability distributions that incorporate the range of parameter values found in the existing scientific and economic literature. Overall, we estimate that moderate climate change will cause average extreme weather damages to increase by tens of billions of dollars per year. However, the confidence intervals surrounding our estimates are very wide, reflecting substantial underlying uncertainties.

This report builds on several previous syntheses of relevant literature. For example, Bouwer (2013) reviews projections of extreme weather losses under climate change in 2040; Kousky (2014) reviews estimates of the costs of extreme weather; Ranson et al (2014) conducts a meta-analysis of the impact of climate change on tropical and extratropical cyclone damages; and Lazzaroni and van Bergeijk (2014) presents a meta-analysis of t-statistics drawn from 64 studies of the macroeconomic impacts of natural disasters. However, to the best of our knowledge, no study has combined the three strands of literature summarized above and used them to parameterize an IAM-compatible damage function.

The remainder of the report is organized as follows. First, in Section 2, we present a simple modeling framework for representing how socioeconomic development and climate change will affect damages from extreme weather. Next, in Section 3, we review evidence on the magnitude of historical losses from extreme weather. In Section 4, we then summarize studies of how losses are affected by socioeconomic development. In Section 5, we discuss the potential effects of climate change on six major categories of extreme weather events. Finally, in Section 6, we parameterize an IAM-compatible damage function based on the results from the previous sections, and use it to project average annual damages from extreme weather under a 2.5°C increase in global surface atmospheric temperature. Section 7 concludes.

2 A Reduced-Form Model of Extreme Weather Losses

In this section, we present a simple model of future damages from extreme weather. The model includes three components that describe how baseline damages vary across geographic areas, how socioeconomic growth affects damages, and how climate change affects damages.

The purpose of the model is to provide a framework for standardizing and combining empirical estimates from the research literature. While our efforts do not rise to the level of a formal meta-analysis, the model does provide a useful organizing framework for the rest of this paper. Sections 3, 4, and 5 are dedicated to reviewing empirical evidence on the three main model components, respectively.

Note that we do not attempt to capture specific causal mechanisms within the model. Instead, we abstract away from particular mediators of the climate change-damage relationship, and focus on the reduced-form relationship between characteristics of the scenario (i.e., location, socioeconomic change, and temperature change) and final projected damages. Overall, our approach draws heavily on the temperature-loss functional forms specified in Narita, Tol, and Anthoff (2009). However, unlike their model, we treat the temperature-damage relationship as a "black box", without attempting to break apart the science and economics.

The model is as follows. Suppose that $D_i(\cdot)$ is a damage function that represents the monetary cost of extreme weather damages in region i of the world. We model damages in year t as a function of three variables: income Y_{it}, population P_{it}, and surface air temperature change ΔT_t:

$$D_i(Y_{it}, P_{it}, \Delta T_t) = \alpha_i \cdot B(Y_{it}, P_{it}) \cdot C_i(\Delta T_t)$$

We decompose this damage function into three multiplicative terms. The first term, α_i, is a coefficient which represents average annual monetary losses in region i, under baseline conditions. The second term, $B(Y_{it}, P_{it})$, captures the effects of income and population growth on damages. The final term, $C_i(\Delta T_t)$, represents the change in damages in region i due to changes in temperature.

Note that this functional form makes several simplifying assumptions. It assumes that the effects of socioeconomic growth and climate change are multiplicatively separable. While reasonable, we acknowledge that this is an empirical question. Additionally, the model assumes that the effects of socioeconomic growth on losses are the same across regions. We model the effects of socioeconomic growth on losses as:

$$B(Y_{it}, P_{it}) = \left(\frac{Y_{it}}{Y_{i0}}\right)^{\lambda} \cdot \left(\frac{P_{it}}{P_{i0}}\right)^{\pi}$$

In this equation, Y_{i0} represents income (or GDP) in the baseline year, and P_{i0} represents population in the baseline year. This functional form assumes that changes in damages are proportional to some power of the ratio of baseline and future income (or population). In other words, the elasticities of losses with respect to income and population are λ and π, respectively. The specification differs from the functional form used in Narita, Tol, and Anthoff (2009, 2010), in that it places no constraint on the relationship between the elasticities with respect to income and population .[1]

The model also makes some simplifying assumptions about the effects of climate change. In particular, we assume that the change in surface air temperature ΔT_t is a sufficient statistic that captures all relevant dimensions of the relationship between climate change and extreme weather. This is a strong assumption,

[1] The functional form used by Narita, Tol, and Anthoff (2009, 2010) implies that $\lambda = 1 - \pi$. Section 4.3 discusses this issue in more detail.

given that extreme weather patterns are likely to be influenced by many aspects of climate change, including increasing sea levels and changing sea surface temperature differentials. However, in our view, the limitations imposed by this assumption are more than justified by the analytical simplicity that it creates. In particular, because most IAMs include only very simplistic representations of climate, including extra parameters would provide little practical value. We model $C_i(\Delta T_t)$ using an exponential functional form:

$$C_i(\Delta T_t) = (1 + \tau_i)^{\Delta T_t}$$

Again, we do not claim that this functional form is exactly correct—in fact, the true relationship is probably highly complex and nonlinear. However, an exponential model is tractable and consistent with recent meta-analysis work (e.g., Ranson et al, 2014). A rough interpretation of this functional form is that a one degree increase in temperature produces a τ_i percent increase in climate damages.

The remainder of this paper is dedicated to reviewing empirical evidence on the parameter values for the three components of the model. In Section 3, we discuss estimates of baseline damages from extreme weather in different regions of the world. In Section 4, we review estimates of the relationship between socioeconomic growth and extreme weather damages. Finally, in Section 5, we present estimates of the relationship between temperature change and extreme weather damages.

3 Historical Extreme Weather Losses

This section of the paper reviews empirical evidence on historical losses from extreme weather events. As discussed in Kousky (2014), extreme weather can cause a wide range of economic impacts. Official tallies are often based on the cost of repairing damaged infrastructure, such as buildings and roads (Guha-Sapir et al, 2015). However, there are many other categories of economic impacts, including mortality (Kahn, 2005), morbidity and psychological costs (Stephens, 2007), economic growth shocks (Felbermayr and Gröschl, 2014), displacement and migration costs (Sacerdote, 2014), deadweight loss from transfer payments (Deryugina, 2013), and defensive expenditures (Crompton and McAneney, 2008; Hsaing and Narita, 2012).

Broadly speaking, the academic literature takes two approaches to quantifying these impacts. First, many studies rely on loss estimates reported by insurance companies, government agencies, and other official sources. These estimates are typically based on summing up reports about individual homeowner and business losses (such as insurance claims). The advantage of this approach is that data on reported losses is readily available for a wide variety of types of natural disasters. However, reported data may be incomplete or inaccurate, and may only focus on certain types of damage (e.g., infrastructure damage).

Second, some papers estimate damages by using panel data to measure how disaster incidence affects important economic outcomes. In these studies, the dependent variable is a measure of economic status, such as GDP, income, employment, or disaster aid. These studies then look for a change in the outcome variable in the years following the occurrence of an extreme event. This change is interpreted as the causal effect of the event. This approach also faces data limitations, but has the key advantages of allowing for a flexible relationship between events and losses, and of being able to measure effects on a wide range of endpoints.

The remainder of this section reviews these two sources of evidence on historical losses. First, in Section 3.1, we review empirical estimates that use reporting data to estimate the economic impacts caused by extreme weather events. Then, in Section 3.2, we discuss economic impact estimates based on panel data. Finally, in Section 3.3, we compare the results from the two approaches and present a summary of baseline losses by geographic region and type of disaster. Our discussion throughout this part of the paper builds on Kousky (2014), which provides an overview of the literature on losses from natural disasters, and on Lazzaroni and van Bergeijk (2014), which presents a meta-analysis of t-statistics drawn from 64 studies of the macro-economic impacts of natural disasters.

3.1 Loss Estimates based on Reporting Data

We begin by describing the results of studies that estimate disaster damages using estimates based on insurance claims and other official sources. Typically, the raw data for these studies is drawn from one of several disaster databases, such as the Centre for Research on the Epidemiology of Disasters (CRED)'s International Disaster Database (EM-DAT), the University of South Carolina's Spatial Hazard Events and Losses Database for the United States (SHELDUS), Swiss Re's NetCat, Munich Re's NatCatSERVICE, Aon Benfield's disaster database, or NOAA's Storm Events database. These databases use loss estimates from a variety of sources, including government agencies, press agencies, research institutes, non-governmental organizations, UN agencies, and insurance companies (Guha-Sapir et al, 2015).

The coverage of these databases is limited based on certain criteria, and may be incomplete. For example, EM-DAT includes information for reported disasters that caused 10 or more mortalities, affected 100 or more people, led to a declaration of a state of emergency, or led to a call for international assistance. The loss estimates in EM-DAT represent direct damages to property, crops, and livestock, but exclude indirect or long-term consequences. In 2003, the recording method for disasters in EM-DAT changed, leading to more disasters being reported in more recent years (Guha-Sapir et al, 2015). Furthermore, in some cases the database may report losses of $0, even though actual damages were not assessed or recorded (Toba, 2009). However, Kousky (2014) shows that at the aggregate level, summing across many different disasters, the four main international databases (Swiss Re, Munich Re, Aon Benfield, and EM-DAT) produce generally similar patterns.

Despite these limitations, disaster databases provide the only practical source of source of relatively comprehensive event-level damages estimates. To illustrate the overall patterns in this reporting data, Table 1 summarizes damage estimates from EM-DAT for the period from 1985 through 2014. The figure presents the number of events, average annual damages, and average annual mortality, by type of disaster and region. The figure shows over the last thirty years, tropical cyclones have been responsible for the greatest component of total losses: approximately $27 billion per year. Of this, $19 billion per year occurred in the United States. Losses from inland floods have also been large, at $23 billion per year. Losses from other types of disasters are smaller: $7 billion per year from small storms, $2 billion per year from both extratropical cyclones and wildfires, and $0.3 billion per year from landslides/avalanches. On the basis of mortality, losses are also higher for tropical cyclones (14,000 deaths per year), followed by inland floods (6,000 deaths per year). Most of these deaths occur in Asia.

Table 1: Average Annual Impacts from Extreme Events, By Region

Continent	Tropical Cyclones	Extratropical Cyclones	Inland Floods	Wildfires	Small Storms	Landslides / Avalanches
	Number of Events, 1985-2014					
North America	417	1	347	97	290	28
South America	9	1	271	30	32	83
Europe	17	101	393	85	104	33
Africa	84	0	649	25	58	29
Asia	686	0	1,207	50	202	291
Australia	121	0	72	24	28	15
World, Total	**1,334**	**103**	**2,939**	**311**	**714**	**479**
	Average Annual Reported Damages (millions, $2013)					
North America	$18,671	$37	$2,549	$1,097	$5,750	$19
South America	$18	$0	$919	$46	$9	$62
Europe	$36	$2,011	$4,388	$528	$563	$97
Africa	$61	$0	$274	$16	$42	$0
Asia	$8,115	$0	$14,572	$552	$678	$141
Australia	$368	$0	$508	$96	$285	$0
World, Total	**$27,269**	**$2,047**	**$23,209**	**$2,336**	**$7,328**	**$319**
	Average Annual Reported Mortality					
North America	1,023	0	221	6	115	24
South America	22	0	1,270	4	9	156
Europe	3	15	94	15	13	34
Africa	87	0	619	9	21	30
Asia	12,467	0	3,514	25	197	560
Australia	25	0	8	8	1	14
World, Total	**13,627**	**15**	**5,725**	**67**	**357**	**818**

Notes: This table is based on data for the 30-year period from 1985 to 2014. Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015). Source for damages: Guha-Sapir et al, 2015

Using data drawn from EM-DAT and other similar sources, a number of authors have developed estimates of annual average losses from extreme weather in different geographies (Collins and Lowe, 2001). For example, Kunkel, Pielke, and Changnon (1999) presents average annual U.S. losses and mortality from eight different categories of extreme weather events. Similarly, Blake, Landsea, and Gibney (2011) presents estimated damages from U.S. hurricanes, based on insurance loss data, and BTE (2001) uses insurance loss records to estimate the cost of cyclones in Australia. Because losses depend on the population and infrastructure at risk, these studies typically use normalization approaches that control for long-term changes in socioeconomic variables, such as population density or housing value. Because of the importance of these variables in predicting future losses, we discuss these studies separately in greater detail in Section 4.

Other studies have used reported loss data to try to understand the relationship between the characteristics of an extreme weather event and the damage that it causes (Pielke and Downton, 2000; Choi and Fisher, 2003; Schmidt et al, 2009a,b; Nordhaus, 2010; Bouwer and Botzen, 2011; Czajkowski, Simmons, and Sutter, 2011; Mendelsohn et al, 2011; Zia, 2012; Deryugina, 2013). This information is useful for planning and insurance purposes. It is also important for predicting future damages from extreme weather, e.g., if climate change results in a shift in the intensity, frequency, or geographic range of extreme weather events. To provide a sense of this strand of literature, we focus here on one issue that has been particularly controversial: the relationship between wind speed and hurricane losses. As Nordhaus (2010) argues, "given the number and complexity of relationships entering the wind speed–damage relationship, it is unlikely that the actual functional parameters can be derived from first principles." Thus, most studies have taken an empirical approach in which they regress reported storm losses (often based on EM-DAT, but sometimes on other databases) on a measure of wind speed.

Table 2 summarizes results from selected studies on this topic. The top panel of the table shows results from studies that estimate damages broken down by Saffir-Simpson hurricane intensity category. This scale is based on the highest sustained wind speed achieved by a storm, and ranges from 74-95 miles per hour for a Category 1 storm, to above 157 miles per hour for a Category 5 storm. For example, Pielke et al (2008) estimate that average normalized damages per storm are $0.1 billion for tropical and subtropical storms, $1.2 billion for a Category 1 hurricane, $2.2 for a Category 2 hurricane, $7 billion for a Category 3 hurricane, $30 billion for a Category 4 hurricane, and $26 billion for a Category 5 hurricane.[2]

Other studies, shown in the bottom panel of Table 2, estimate results as parametric functions of wind speed. The estimated relationship between wind speed and damages varies considerably across these studies. For example, estimates of the percentage change in damage that results from a one knot increase in wind speed include +2.8% (Schmidt et al, 2008b), +3.1% (Felbermayr and Gröschl, 2014), +4.0% (Czajkowski et al, 2011), +6.3% to +8.2% (Bouwer and Botzen, 2011), and +9.4% (Nordhaus, 2010). These semi-elasticities imply considerably different impacts, particularly for the strongest storms.

Although most of the studies in Table 2 use reported losses as their dependent variable, a few calculate losses based on observable economic indicators (such as GDP). We describe these studies in more detail in the next section.

[2] Note that the Pielke et al (2008) dataset includes only three Category 5 storms, and so their damage estimate for this category is very imprecisely estimated.

Table 2: The Impact of Wind Speed on Tropical Cyclone Damages

				Saffir-Simpson Storm Category					
Study	**Outcome Variable**	**Geography and Time Period**	**Relationship to Wind Speed**	**TS/ STS**	**1**	**2**	**3**	**4**	**5***
Results by Saffir-Simpson Category									
Collins and Lowe, 2001	Damage (normalized, billions)	U.S., 1900-1999		-	0.12	0.64	1.99	10.53	2.07
Pielke et al, 2008	Damage (pop. norm., billions)	U.S., 1900-2005		0.14	1.12	2.24	7.00	29.96	26.42
Pielke et al, 2008	Damage (prop. norm., billions)	U.S., 1900-2005		0.14	1.25	2.24	7.02	28.45	26.47
Zylberberg, 2012	GDP growth per 1% of pop. exposed	180 countries, 1980-2006		-	-0.001	-0.013	-0.038	-0.060	-0.128
Deryugina, 2013	Log damages	Gulf / Atlantic U.S., 1970-2006		-	2.75	3.58	5.02	5.47	
Deryugina, 2013	Per capita damages	Gulf / Atlantic U.S., 1970-2006		-	73	53	732	629	
Deryugina, 2013	Log flood insurance payments	Gulf / Atlantic U.S., 1970-2006		-	1.74	2.60	3.94	3.11	
Results as a Function of Wind Speed									
Schmidt et al, 2008b	Damages	U.S., 1950-2005	+2.8% per knot						
Nordhaus, 2010	Damages	U.S., 1900-2008	+9.4% per knot						
Bouwer and Botzen, 2011	Damages	U.S. , 1900-2005	+6.3% to +8.2% per knot						
Anttila-Hughes and Hsaing, 2011	Household income	Philippines	-22% per m/s of WS exposure						
Czajkowski et al, 2011	Fatalities	U.S., 1970-2007	+4% per knot						
Mendelsohn et al, 2011	Damages	U.S., 1960-2008	+5.0% per +1% increase in WS						
Strobl, 2011	Damages	U.S., 1970-2005	+3.2% per +1% increase in WS						
Zia, 2012	Damages	U.S., 1900-2005	+267% to +395% per storm category						
Felbermayr and Gröschl, 2014	Damages, Fatalities	World, 1979-2010	+3.1% damage and +1.5% killed per knot						
Hsaing and Jina, 2014	GDP 15 years after event	World	-0.38% per m/s of WS exposure						

*Notes: Categories on the x-axis represent the Saffir-Simpson wind scale, with wind speeds of 74-95 mph (Category 1), 96-110 mph (Category 2), 111-129 mph (Category 3), 130-156 mph (Category 4), and 157 mph or higher (Category 5). The TS/STS category includes tropical and subtropical storms that never reached hurricane intensity. *Note that only three Category 5 hurricanes made landfall in the United States between 1900 and 2005.*

3.2 Loss Estimates based on Event Studies

Disaster databases such as EM-DAT provide a practical, easily-accessible source of information about direct damage from extreme weather events. However, these databases suffer from a number of known coverage and accuracy issues, and omit many potentially important categories of costs. In this subsection, we review an alternative source of empirical evidence: econometric studies of how disasters affect observable macroeconomic economic indicators. We begin in Section 3.2.1 by summarizing several competing theories about how extreme weather events could affect economies. Next, in Section 3.2.2, we discuss the range of empirical approaches that studies have used to test those theories. Then, in Section 3.2.3, we review main empirical macroeconomic findings from the literature. Finally, in Section 3.2.4, we discuss some relevant evidence from microeconomic studies of extreme weather impacts.

3.2.1 Hypotheses about the Macroeconomic Effects of Disasters

Generally speaking, the literature contains three main competing hypotheses about the macroeconomic impacts of disasters: "transitory impact", "permanent loss", and "creative destruction" (Hsaing and Jina, 2014). All of these hypotheses can be motivated by a simple neoclassical growth model, in which there are two factors of production (labor and capital) that evolve over time following an optimal path. The key question is how this model responds to an external capital shock caused by a disaster.

Under the "transitory impact" hypothesis, a disaster causes a short-term loss of consumption, but in the long term the economy will recover to its pre-disaster growth path. One way to model this hypothesis is to assume that capital has declining returns to scale. Under this assumption, the negative capital shock caused by a disaster will temporarily move an economy away from its equilibrium growth path. However, if labor supply remains constant after the disaster, then the loss of capital will lead to an increase in the marginal product of capital. As a result, in the years following the shock the economy will invest more and grow faster than it otherwise would have, eventually catching up to its long-term output path. Overall, the disaster will be costly for the economy, since it will experience a temporary loss of output, but the impact will be transitory.

Under the "permanent loss" hypothesis, the economy never recovers to its pre-disaster output path, but instead grows on a parallel but lower trajectory. This hypothesis can be justified in several ways, for example, if the economy exhibits constant (or near-constant) returns to scale. Under this assumption, the loss of capital caused by a disaster does not affect the marginal product of capital, and so the economy has no incentive to sacrifice short-term consumption in order to make compensating investments that would bring it back to its pre-disaster growth path.

Finally, under the "creative destruction" hypothesis, the economy experiences a temporary loss of output but then rebounds back to an even higher growth curve. This Schumpeterian hypothesis is motivated by a model in which technology (i.e., the marginal product of capital) improves over time. As a result, capital investments become outdated, and so the opportunity to rebuild following a disaster can actually provide a net long-term benefit to the economy. There is some empirical evidence that supports this theory in other contexts. For example, Hornbeck and Keniston (2014) find that immediately after the Great Boston Fire of 1872, land values in the area that was destroyed increased substantially relative to similar surrounding areas. They argue that substantial positive externalities were created when property owners had the opportunity to rebuild simultaneously. However, the creative destruction hypothesis also implies that communities would benefit from choosing to destroy and rebuild their own infrastructure, a controversial proposition that has met with mixed empirical support (Collins and Shester, 2013; Chen and Yeh, 2013).

3.2.2 Empirical Strategies for Estimating Losses

To test the macroeconomic theories described in the previous section, researchers have used several different empirical strategies to estimate how disasters affect observable economic indicators. One category of studies examines the cross-sectional relationship between disaster frequency and economic growth (Skidmore and Toya, 2002; Kim, 2010). In these studies, the dependent variable is a measure of long-term economic growth, and the independent variable is some measure of exposure to extreme weather events. For example, Skidmore and Toya (2002) calculate long-term average GDP growth rates over the period from 1960 to 1990, for each of 89 different countries. They then regress average growth rates on the total number of climatological and geological disasters experienced by each country over that time period. Their results suggest that climatological disasters are associated with positive growth, while geological disasters are associated with negative growth.

A primary limitation of these cross-sectional studies is that it is difficult to assess the direction of causality. In particular, it is possible that some omitted variable—such as latitude—may have a causal influence on both the frequency of disasters and economic growth experienced by a country. Because of this concern, a second category of studies uses event study or differences-in-differences approaches to measure how important economic variables—such as GDP, taxable sales, income, and employment—change in the years following an extreme weather event (e.g., Murlidharan and Shaw, 2003). Since the timing and location of major weather events is presumably random, a before-after comparison can plausibly reveal the causal effect of the disaster on the outcome variable of interest. Section 3.2.3, below, summarizes empirical results from this literature.

One important methodological question for studies of disaster impacts is how to project counterfactual growth in the absence of a disaster. Studies use a variety of approaches. For example, Hochrainer (2009) uses an autoregressive integrated moving average (ARIMA) model to project how GDP would have evolved in the countries affected by 225 major disasters that occurred between 1960 and 2005, had those disasters not occurred. By comparing this predicted change in GDP versus actual observed GDP, the study estimates that five years after a disaster, a country's GDP will have declined by 2.0% on average (with a median decline of 4.0%), relative to what it would have been without the disaster. A number of other studies have also used autoregressive time series approaches (e.g., Fomby, 2013; Raddatz, 2006). For example, using vector auto-regression techniques, Cuñado and Ferreira (2011) find that major floods cause an increase in GDP growth in developing countries, but have no effect in developed countries. Another common approach to projecting counterfactual growth is to use panel techniques that allow for common shocks across countries. For example, Hsaing and Jina (2014) use a differences-in-differences approach, in which they model GDP levels as a function of country fixed effects, year fixed effects, and hurricane wind speed variables. Strobl (2011) uses a panel regression with time fixed effects and a spatially autoregressive error term to estimate how hurricane landfalls affect local GDP growth in a dataset consisting of 409 U.S. counties between 1970 and 2005.

Another important consideration for this literature is how to represent the intensity of extreme weather events. Many older studies use simple binary or count variables that indicate whether a particular country experienced an extreme event in a particular year. However, as shown in the previous section, the characteristics of an extreme event are important determinants of the damage it causes. Furthermore, even a large hurricane or flood could cause relatively little damage if it were to strike an unpopulated area. To address this issue, some studies have used reported damages as a measure of event intensity (e.g., Bluedorn, 2005). However, one drawback of this approach is that reported damages are imperfectly measured, which could result in downward biased impact estimates if they are used as an independent variable. To illustrate this problem, Zylberberg (2012) estimates the impacts of EM-DAT hurricane damages on GDP growth using two-stage least squares, in which the first stage involves using hurricane category dummy variables as instruments for reported EM-DAT damages. The TSLS results show that reported hurricane damages of one percent of GDP result in a 0.4 percentage point loss of GDP growth, which is an order of magnitude larger than the corresponding OLS estimate (without instrumenting for damages). In part due to this concern, recent studies have begun to represent extreme weather intensity using spatially-weighted physical measures based on storm models. For example, to represent hurricane intensity, Strobl (2012) uses a population-weighted wind field model. Similarly, Anttila-Hughes and Hsaing (2011) and Hsaing and Jina (2014) represent hurricane intensity using the average of the maximum modeled wind speed experienced per year per pixel, across all geographic pixels in a country.

3.2.3 Summary of Impact Estimates from Macroeconomic Studies

Table 3 summarizes the results from a selected set of studies that use panel econometric techniques to estimate the effects of extreme weather events on macroeconomic indicators. The table presents results for three main categories of events: tropical cyclones, inland floods, and the broader category of "multiple disasters" (since many studies pool together different types of weather-related and non-climatic disasters). We consider what this literature implies about how each of these types of disasters affects short-term economic outcomes, long-term economic outcomes, and transfer payments.

Short-term Effects

We begin by reviewing the short-term effects of tropical cyclones, floods, and disasters.

Many of the studies in the top panel of Table 3 find that GDP levels decrease or GDP growth slows in the year or two following a major hurricane (Bluedorn, 2005; Strobl, 2011; Strobl, 2012; Zylberberg, 2012; Felbermayr and Gröschl, 2014; Hsaing and Jina, 2014). However, several studies find that hurricanes have no statistically-significant impact on GDP (Benson, 1997; Hsaing, 2010; Loayza et al, 2012; Fomby, Ikeda, and Loayza, 2013). One study (Ramcharan, 2007) estimates that hurricanes have a small positive effect on GDP.

For flooding, the evidence is even more mixed. Of the six studies included in the second panel of the table, two find that flooding has a negative effect on GDP growth (Pauw et al, 2011; Ghimire and Ferreira, 2013), one finds no effect (Felbermayr and Gröschl, 2014), and three find a positive effect (Cuñado and Ferreira, 2011; Loayza et al, 2012; Fomby, Ikeda, and Loayza, 2013). In both Cuñado and Ferreira (2011) and Fomby, Ikeda, and Loayza (2013), the positive effects are only present in developing countries.

Finally, in studies that look at the effects of multiple disaster types combined, the same mixed pattern appears. Some studies find significant negative results, but many cannot reject the null hypothesis of no effect, and a few find positive effects.

Overall, these short-term results are consistent with a recent meta-analysis by Lazzaroni and van Bergeijk (2014), in which the authors analyze 64 studies of the macro-economic impacts of natural disasters. In their sample, 36 studies examined determinants of reported losses from disasters, and 33 used econometric techniques to estimate the impacts of disasters on GDP. The dependent variable for the meta-analysis is the t-statistic associated with the effect of the disaster on losses, as reported in each study. The authors find that studies of reported losses tend to find that disasters have significant negative effects, but that studies of GDP find an effect that is not statistically different from zero.

One additional pattern that does seem to emerge across a variety of contexts is that extreme weather events have effects that vary across sectors (Fomby, Ikeda, and Loayza, 2013). The agricultural sector often shows strong negative effects, while the construction sector can actually benefit from hurricane exposure (Hsaing, 2010). For example, Baade, Baumann, and Matheson (2007) found that taxable sales in Miami increased substantially in the months following Hurricane Andrew, presumably reflecting reconstruction efforts.

Long-term Effects

While there is still some uncertainty in the literature about the short-term macroeconomic effects of extreme weather events, even more unclear is what happens in the longer-term. Many studies use empirical strategies that are not well-suited for measuring long-term effects. For example, authors often focus on only a short time horizon, or use autoregressive functional forms that assume conditional convergence over time (e.g., Strobl, 2012).

A few studies have tried to measure longer-term effects. For example, Loayza et al (2012) concludes that hurricanes have no effect on average five-year growth rates following a storm. However, Zylerberg (2012) finds that hurricanes cause an immediate loss of GDP growth, with no evidence of recovery to trend within five years. Using a differences-in-differences approach with a panel that includes every world country from 1950 to 2008, Hsaing and Jina (2014) find that hurricanes have very large negative long-term impacts. Their estimates imply that twenty years after a 90th percentile storm, a country's per capita income is lower by 7.4% than it otherwise would have been.

Transfer Payments

One challenge related to measuring the impacts of major extreme weather events is that the costs of these disasters are not borne entirely by people who live in the affected area. Instead, there are a variety of formal and informal mechanisms—including insurance payments and disaster aid—for distributing the costs across a wider economic area.

One very robust finding from the literature is that areas that are hit by extreme events receive additional aid. While this sometimes takes the form of aid explicitly labeled as disaster aid, transfer payments also include a broader variety of social safety nets. For example, Deryugina (2013) estimates that over the ten years following a hurricane landfall in the United States, total non-disaster transfer payments (such as unemployment benefits) are twice as large as official disaster transfer payments. In the international context, Stromberg (2007) finds that countries that experience more severe disasters receive more international aid. However, aid is influenced both other factors as well, including proximity, media coverage, and common language (Stromberg, 2007). Similarly, in an analysis of Vietnamese natural disasters, Noy and Vu (2011) find that some regions of the country are more likely to receive disaster aid than others.

Transfer payments may also play a role in post-disaster recovery (Stromberg, 2007). For example, Von Peter et al (2012) find that by ten years after an uninsured major natural disaster, GDP is 2.3 percent lower than it otherwise would have been. However, if that disaster occurred in a country with high insurance penetration rates, there is no effect on GDP. Similarly, Melecky and Raddatz (2011) find that the impacts of disasters are lower in countries with high rates of insurance penetration. These results suggest that the endogeneity of insurance and post-disaster aid may explain part of the disagreement in the literature over the sign of the impacts of large-scale extreme weather events.

Table 3: Panel Studies of Macroeconomic Losses from Extreme Weather

Study	Geography and Time Period	Average Disaster Impacts
Tropical Cyclones		
Benson, 1997	Fiji, 1970-1995	Typhoons and droughts cause an immediate 1.9% decrease in GDP growth rate (although not significantly different from zero)
Bluedorn, 2005	26 Central American countries, 1960-2002	GDP growth decreases 5.4% following a year with hurricane losses of 100% of GDP, and then returns to steady-state rate
Baade, Baumann, and Matheson, 2007	Miami MSA, 1980-2005	Taxable sales fell 3.3% below baseline in the month Andrew hit, increased 5.5% above baseline the following month, and declined back to baseline over next 18 months.
Ramcharan, 2007	55 developing countries, 1961-2000	Per capita GDP growth is 1.0% higher the year after a storm in countries with flexible exchange rates, but is unaffected in countries with fixed exchange rates
Hsaing, 2010	28 Caribbean countries, 1970-2006	Hurricanes have no statistically significant effect on GDP, but they do affect the wholesale/retail/restaurant sector (-0.9%), agricultural sector (-1.8%), and construction sector (+1.4%).
Anttila-Hughes and Hsaing, 2011	82 Philippines provinces, 1978-2008	Typhoons depress average annual Filipino household income by 6.7%, household expenditures by 7.1%, and cause 1.1 female infant deaths per 1,000 households.
Strobl, 2011	409 U.S. counties, 1970-2005	GDP growth is 4.5 percentage points lower the year of a hurricane, and then recovers to normal growth rates.
Coffman and Noy, 2012	Hawaiian islands, 1975-2011	Hurricane Iniki caused a permanent 15% decrease in private-sector jobs and hotel rooms; a spike in transfer payments in year after the hurricane; and possibly a slow decline in population and per capita income
Zylberberg, 2012	180 countries, 1980-2006	Hurricanes causes decreases in GDP growth, e.g., -0.13 percentage points for every 1% of population exposed to a category 5 hurricane. No evidence of catch-up growth.
Loayza et al, 2012	94 countries, 1961-2005	The five-year average annual GDP growth rate decreases by a statistically insignificant 0.1 percentage points after a storm.
Strobl, 2012	32 Caribbean and Central American nations, 1950-2006	The average hurricane strike reduces GDP by 0.83 percentage points.
Fomby, Ikeda, and Loayza, 2013	84 countries; 1960-2007	Severe storms (including hurricanes) have no statistically significant effect on GDP growth in either developed or developing countries.
Deryugina, 2013	Eastern and Gulf coasts of U.S., 1970-2006	Over ten years following a hurricane, non-disaster transfer payments are 2-3% higher ($750 per capita), almost double disaster transfer payments ($356 per capita).
Felbermayr and Gröschl, 2014	108 countries, 1979-2010	GDP decreases by 0.16% in the year that a storm makes landfall
Hsaing and Jina, 2014	All world countries, 1950-2008	Twenty years after a storm, per capita economic output is 0.37% lower for every meter/second (2.2 miles/hour) increase in nationally-averaged maximum wind speed per year.
Inland Floods		
Cuñado and Ferreira, 2011	118 countries; 1985-2008	Flooding causes 1.5% increase in GDP growth two years after event. This effect is driven by developing countries.
Fomby, Ikeda, and Loayza, 2013	84 countries; 1960-2007	Flooding has a small, marginally significant positive effect on GDP growth in developing countries, totaling 0.6 percentage points after four years. It has no effect in developed countries.
Pauw et al, 2011	Malawi, 1982-2004	Using a hybrid empirical/simulation methodology, predicts average annual GDP losses of 0.70% from flooding
Loayza et al, 2012	94 countries, 1961-	The five-year average annual GDP growth rate increases 1.0

Table 3: Panel Studies of Macroeconomic Losses from Extreme Weather

Study	Geography and Time Period	Average Disaster Impacts
	2005	percentage points after a typical flood
Ghimire and Ferreira, 2013	125 countries, 1985-2009	A major flood reduces GDP growth by 2.3% and increases the probability of conflict incidence by 8.5%.
Felbermayr and Gröschl, 2014	108 countries, 1979-2010	Unusually high rainfall reduces GDP by a statistically insignificant 2.4%.
Multiple Disasters		
Albala-Bertrand, 1993	26 countries; 1960-1979	Disasters have a slight positive impact on GDP growth
Charveriat, 2000	20 Latin American/ countries, 1980-1996	Real median GDP falls 2% in year after disaster, but then increases +3% in two following years
Choi and Fisher, 2003	U.S., 1929-1998	N/A (dependent variable is reported losses)
Tvares, 2004	World countries; 1987-2001	One year after a disaster, growth of real GDP per capita decreases by 0.6% to 5.7%.
Caselli and Malhotra, 2004	World; 1975-1996	Disasters have no effect on GDP growth, except for those that involve high mortality
Raddatz, 2006	World (developing); 1965-1997	2% decline in real output one year after event; no effect after five years (includes droughts, extreme temperature, wind storms, inland floods)
Noy, 2009	109 countries; 1970-2003	+1 SD in direct damages reduces GDP growth by 9% in developing countries and by 1% in developed countries.
Hochrainer, 2009	225 major disasters; 1960-2005	Five years after a major storm that causes reported damages of >1% of GDP, GDP is 2% lower on average.
Noy and Vu, 2010	61 provinces in Vietnam, 1995-2006	+1% increase in damage/output increases output growth by +0.03%
Vu and Hammes, 2010	China	+1% increase in mortality decreases output by 47 billion Yuan ($7.4 billion), but with no effect on growth. +1% increase in damage reduces output growth by 0.24%.
Von Peter et al, 2012	203 countries, 1960-2011	Uninsured natural disasters reduce GDP by 2.3% after ten years. Insured natural disasters have no effect on GDP.
Cavallo et al, 2013	196 countries; 1970-2008	Natural disasters have no significant effect on short-term or long-term economic growth
Baker and Bloom, 2013	60 countries, 1970-2013	Natural disasters have no significant effect on stock market levels or volatility

Notes: The table excludes a number of other studies of the effects of multiple disaster types combined, including Stephens (2007), Heger et al (2008), Raddatz (2009), Hallegate, 2009, Jaramillo (2009), Vogel (2011), Sawada et al (2011), Noy and Nualsri (2011), Shimada (2012), Bergholt and Lujala (2012), Ahlerup (2013), Felbermayr and Gröschl (2013), and McDermott, Barry, and Tol (2014) . It also excludes Jackson (2013), which focuses on droughts.

3.2.4 Summary of Impact Estimates from Microeconomic Studies

In addition to the large literature on macroeconomic outcomes, a few studies have estimated the impacts of extreme weather events using panels of individual-level data. For example, Deryugina, Kawano, and Levitt (2014) use a panel of U.S. tax return data to track taxpayers who were affected by Hurricane Katrina. They find that although Katrina caused an immediate decrease in wages and employment, victims of the storm used withdrawals from retirement accounts to offset short-term loss of income. Furthermore, within a few years, affected individuals had higher incomes than similar individuals in cities that were not affected by the storm.

In a different study, Sacerdote (2014) finds that Hurricanes Katrina and Rita caused a substantial short-term drop in the test scores of affected public school students. However, evacuees from the lowest-performing New Orleans schools actually experienced a subsequent net increase in their test scores, presumably due to their forced move to a better educational environment.

Finally, Leiter, Oberhofer, and Raschky (2009) use data on European firms affected by flooding to estimate how floods affect firm-level assets, employment, and productivity. They find that floods cause a short-run increase in assets and employment, but cause a decrease in productivity.

These studies provide valuable insights into the mechanisms that may drive the macroeconomic effects of extreme weather. However, due to space limitations, we do not review this part of the literature in detail.

3.3 Summary of Parameter Estimates

The previous subsections have presented a variety of estimates of how extreme weather damages vary by geography. In this subsection, we draw on that data to develop parameter values that can be used in the modeling framework from Section 2.

Our judgment is that there is not yet sufficient agreement in the literature to draw strong conclusions from macroeconomic studies of the impacts of extreme weather. Some studies estimate that disasters have very large negative effects on GDP, but others find no effect or even positive effects. Furthermore, the time pattern of estimated losses varies substantially across studies. For these reasons, we develop estimates of baseline losses by drawing on disaster reporting data from the EM-DAT database.

Table 4 presents the results of this analysis. For each of the twenty-three regions specified in the EM-DAT database, we calculate average annual losses for each type of extreme weather event. We base these calculations on the thirty-year time period from 1985 to 2014. The patterns in Table 4 are quite similar to the patterns from Table 1. Losses are largest for tropical cyclones and inland floods. The regions with the highest losses are Northern America and Eastern Asia.

Note that the left-hand column of Table 4 assigns a coefficient name to each estimate. For example, α_{NA1} represents baseline losses in Northern America. These coefficients can be used to parameterize the loss equation described in Section 2.

Table 4: Parameters Representing Average Annual Extreme Weather Damage

	Region	Tropical Cyclones	Extra-tropical Cyclones	Inland Floods	Wildfires	Small Storms	Landslides and Avalanches
	North America						
α_{NA1}	Northern America	$15,668	$37	$2,325	$1,088	$5,699	$1
α_{NA2}	Central America	$1,609	$0	$188	$9	$1	$18
α_{NA3}	Caribbean	$1,394	$0	$35	$0	$50	$0
	South America						
α_{SA1}	South America	$18	$0	$919	$46	$9	$62
	Europe						
α_{EU1}	Western Europe	$0	$1,456	$1,157	$0	$396	$56
α_{EU2}	Northern Europe	$14	$437	$847	$5	$98	$0
α_{EU3}	Southern Europe	$15	$99	$1,372	$440	$48	$41
α_{EU4}	Eastern Europe	$6	$18	$1,012	$83	$22	$0
	Africa						
α_{AF1}	Northern Africa	$0	$0	$109	$0	$10	$0
α_{AF2}	Western Africa	$0	$0	$35	$0	$0	$0
α_{AF3}	Eastern Africa	$61	$0	$49	$0	$0	$0
α_{AF4}	Middle Africa	$0	$0	$1	$0	$0	$0
α_{AF5}	Southern Africa	$0	$0	$81	$16	$32	$0
	Asia						
α_{AS1}	Russian Fed.	$0	$0	$47	$0	$1	$24
α_{AS2}	Central Asia	$0	$0	$30	$0	$0	$12
α_{AS3}	Western Asia	$183	$0	$213	$12	$14	$1
α_{AS4}	Eastern Asia	$5,999	$0	$9,052	$94	$539	$93
α_{AS5}	Southern Asia	$844	$0	$3,092	$0	$124	$3
α_{AS6}	South-Eastern Asia	$1,089	$0	$2,139	$447	$1	$7
	Australia						
α_{AU1}	Australia and NZ	$261	$0	$496	$96	$285	$0
α_{AU2}	Melanesia	$32	$0	$10	$0	$0	$0
α_{AU3}	Micronesia	$31	$0	$0	$0	$0	$0
α_{AU4}	Polynesia	$44	$0	$2	$0	$0	$0

Notes: This table is based on data for the 30-year period from 1985 to 2014. Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015). Source for damages: Guha-Sapir et al, 2015

4 The Effects of Socioeconomic Growth on Extreme Weather Losses

As shown in the previous section, average damages from extreme weather vary considerably across regions. Much of this variation is due to differences in exposure, e.g., because tropical cyclones or inland flooding occur only in certain geographic areas. However, an equally important determinant of losses is socioeconomic development. There is broad academic agreement that the steep upward trend in disaster losses over the last century has been driven primarily by increases in the population and infrastructure located in exposed locations (Pielke et al, 2008; Kousky, 2014). Furthermore, at least in the cross-section, nations with higher levels of development experience reduced mortality from disasters (Kahn, 2005). Accounting for these effects in IAMs is important, due both to the long time periods considered by these models and to the fact that any additional damages from climate change may have a proportional effect on future baseline losses.

To gather data that can be used to improve the representation of future baseline extreme weather losses, this section of the paper reviews evidence on how changes in population and economic growth affect losses from extreme events. We begin in Section 4.1 by presenting data on trends in extreme weather losses over time. Then, in Section 4.2, we review empirical studies of the historical relationship between losses and socioeconomic variables. Finally, in Section 4.3, we draw on that literature to develop simple parametric models of the effect of population and economic growth on extreme weather damages.

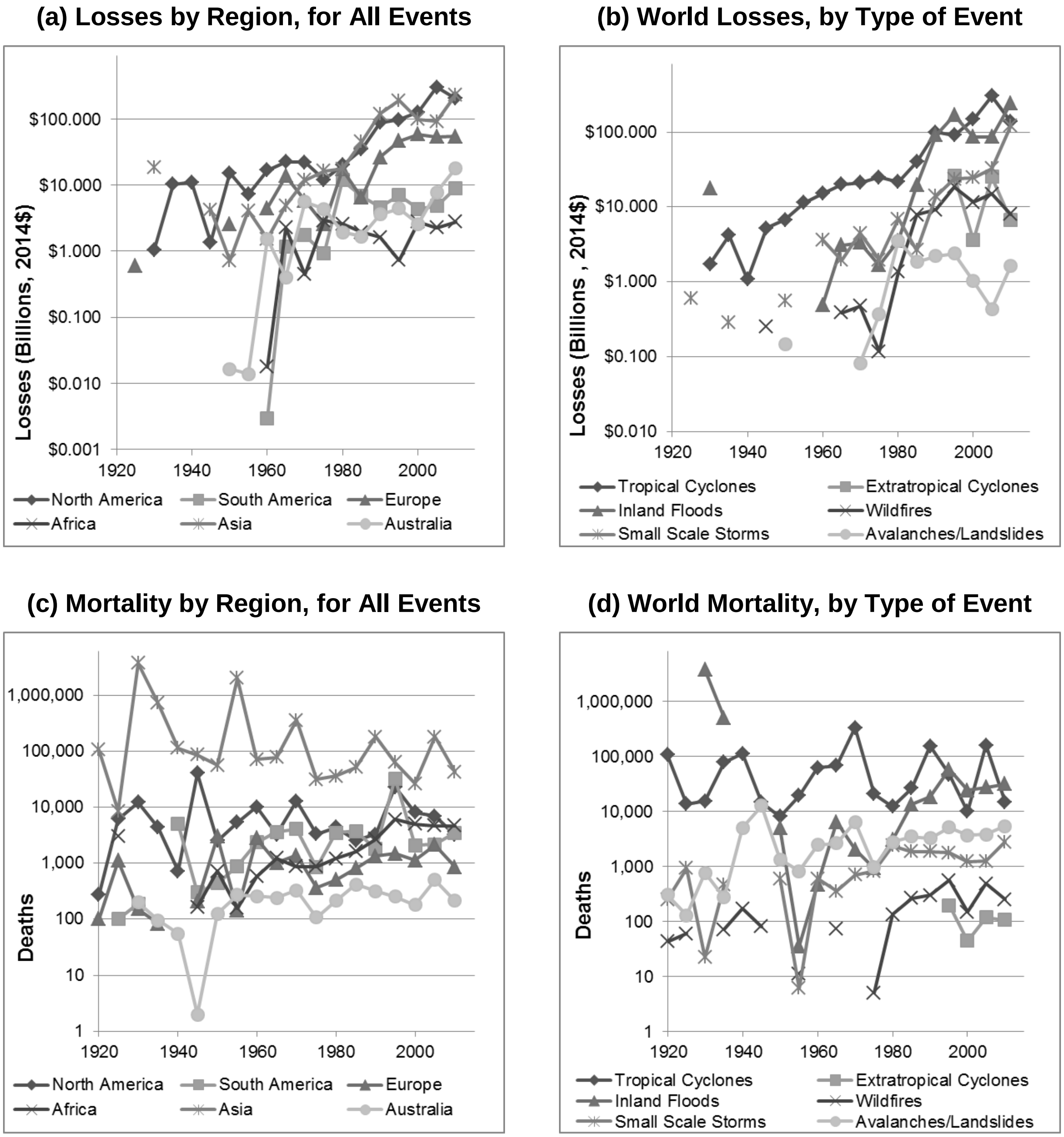
4.1 Historical Trends in Losses

Over the last hundred years, losses from extreme weather have moved steadily upward. To illustrate this trend, Figure 1 presents total losses and mortality over time, by world region and type of event. Panel (a) of the figure shows that between 1920 and 2014, extreme weather losses increased by orders of magnitude in every region of the globe. Panel (b) shows a similar pattern across different types of extreme weather events, with all categories of weather showing large increases.

Panels (c) and (d) of the figure presents trends in mortality from extreme events, by geography and type of event, respectively. The panels demonstrate that over the last century, mortality has increased moderately in many regions, and for most types of disasters. However, the rate of the observed increases is substantially lower than the rate at which extreme weather damages have been increasing. Many potential hypotheses could explain this pattern, including better weather forecasting, improved preparedness and emergency response systems, and general advances in health care.

In interpreting the trends in Figure 1, it is important to recognize that the quality of the EM-DAT data have improved over time, and so much of the apparent increase in losses in the figure is likely due to more comprehensive reporting. Furthermore, extreme weather is highly stochastic, with losses and mortality varying considerably from year to year. Nonetheless, the broader research literature consistently finds compelling evidence that absolute losses from most types of disasters have followed an upward trend (Pielke et al, 2008; Crompton and McAneney, 2008; Barredo, 2009).

Figure 1: Trends in Losses and Mortality from Extreme Weather, 1920-2014



Source: EM-DAT (Guha-Sapir et al, 2015). These graphs should be interpreted with caution, since the completeness of disaster reporting has improved substantially over time.

The sharp increase in losses in recent years has encouraged a number of authors to investigate potential causes. One prominent strand of this literature uses an informal approach that involves examining whether trends in normalized extreme weather losses increase over time (Pielke and Landsea, 1998; Pielke et al, 2008; Crompton and McAneney, 2008; Barredo, 2009; Barredo, 2010; Gall et al, 2011; Barredo et al, 2012; Sander et al, 2014). These studies typically normalize a time series of historical damages by dividing by some combination of socioeconomic variables, e.g., population, GDP, and/or housing values. They then plot the normalized damages over time relative to a base year, with the goal of testing for the presence of a statistically-significant residual trend. In these studies, the authors argue that the absence of any trend is evidence that the normalization variables explain all of the recent increase in losses—and that other factors such as global warming have not affected losses (Pielke et al, 2008).

Table 5 summarizes results from some of these normalization studies. The table shows that after normalization, most of this selected sample of studies find no clear trend in losses over time. This pattern appears to be consistent over a range of disaster types and geographic areas. However, although a normalization approach may be a useful way of illustrating trends in losses over time, studies that use this approach suffer from some econometric drawbacks. One issue is how well the outcome variable chosen approximates actual damages from the extreme event. For example, Barredo et al (2012) relies on insurance surcharges as a proxy for changes in exposure of assets to floods, but notes that changes in surcharges over time depend on insurance penetration, which could change over time independently of other variables.

Another major limitation is these studies implicitly assume that damages have unit elasticity with respect to the socioeconomic variables used for normalization. To see this, consider the simple model of damages presented in Section 2:

$$D(Y, P, \Delta T) = \alpha \cdot \left(\frac{Y}{Y_0}\right)^{\lambda} \cdot \left(\frac{P}{P_0}\right)^{\pi} \cdot C(\Delta T)$$

In this model, damages D depend on economic output Y, population P, and some function of the global change in temperature $C(\Delta T)$. Normalizing damages by output and population gives the following equation:

$$\frac{D(Y, P, \Delta T)}{Y \cdot P} = \alpha \cdot Y_0^{-\lambda} \cdot P_0^{-\pi} \cdot Y^{\lambda-1} \cdot P^{\pi-1} \cdot C(\Delta T)$$

Clearly, economic output and population drop out of the right-hand side of the equation only if the elasticities λ and π both equal 1. Thus, even if normalized damages show no trend over time, it is difficult to conclude that the absence of a trend indicates that climate change has had no effect on losses. For example, if the elasticities λ and π are both less than one, then any effect of climate change via $C(\Delta T)$ would be confused with the remaining effects from economic and population growth. Furthermore, if either economic growth or population were omitted from the normalization, then the equation would suffer from omitted variable bias.

Because of the limitations of the normalization approach, the next subsection reviews studies that use formal regression models to estimate the impacts of socioeconomic variables on losses from extreme weather.

Table 5: Studies of Trends in Normalized Extreme Weather Losses

Study	Disaster Type	Geography & Time Period	Variables	Results
Pielke and Landsea, 1998	Tropical cyclones	U.S., 1925-1995	Inflation, wealth (fixed reproducible tangible wealth), and coastal population	Do not find an increasing trend
Pielke et al, 2008	Tropical cyclones	U.S., 1900-2005	Inflation, wealth (current-cost net stock of fixed assets and consumer durable goods), and coastal population or coastal housing units	Do not find an increasing trend
Barredo, 2010	Extratropical cyclones	Europe, 1970-2008	Inflation, population, wealth (GDP), and purchasing power parity (PPP)	Do not find an increasing trend
Barredo, 2009	Floods	Europe, 1970-2006	Inflation, population, wealth (GDP), and purchasing power parity (PPP)	Do not find an increasing trend
Barredo et al, 2012	Floods	Spain, 1971-2008	Exposed assets (measured separately by insurance surcharges and dwelling values)	Do not find statistically significant trend
Sander et al, 2014	Thunderstorms	Eastern U.S., 1970-2009	Inflation, wealth, population	Pattern consistent with climate forcing
Crompton and McAneney, 2008	Multiple disasters (tropical cyclones, floods, thunderstorms, hailstorms, & bushfires)	Australia, 1967-2006	Occupied dwellings in urban center/locality, dwelling value in state/territory, and tropical cyclone Wind Code adjustment	Do not find an increasing trend
Gall et al, 2011	Natural hazards	U.S., 1960-2009	Inflation, population, and wealth	Find an increasing trend

Notes: This table presents results from selected studies. Other relevant studies include Pielke and Downton (2000), Schmidt et al (2009c), Pielke et al (2002), Pielke et al (2003), and others listed in Bouwer (2010).

4.2 Determinants of Historical Losses

This section reviews evidence on how the socioeconomic characteristics of a particular geographic area affect the damages that it experiences from extreme weather. We consider two measures of damages. First, in Section 4.2.1, we review recent studies of the determinants of weather-related economic losses. Then, in Section 4.2.2, we review studies of the determinants of weather-related mortality.

4.2.1 Determinants of Economic Losses

A number of studies utilize historical data to conduct regression analyses that estimate the impact of socioeconomic growth on damage from extreme weather events. These studies combine data on historical extreme weather events (e.g. hurricane category) with socioeconomic data (e.g. population) to determine the extent to which each variable contributes to the variability of damages across events or years.

Table 6 summarizes selected studies that use regression-based approaches to estimate the contribution of socioeconomic variables to changes in extreme weather losses. Overall, there is consensus in this literature that damages from extreme weather events are influenced by a variety of socioeconomic and regulatory factors, ranging development of coastal areas to changes in building codes/construction techniques (Burton and Hicks, 2005; Emanuel, 2011; Pielke et al, 2008; Ranger and Niehörster, 2011). However, there remains consider disagreement about the magnitude of the effects of specific socioeconomic factors on damages. For example, Cole, Macpherson, and McCullough (2010) compares four different hurricane wind insurance loss models for Florida, and finds that predicted average annual losses have different relationships with housing, insurance, and mitigation in the different models.

Table 6: Studies of Socioeconomic Growth and Extreme Weather Losses

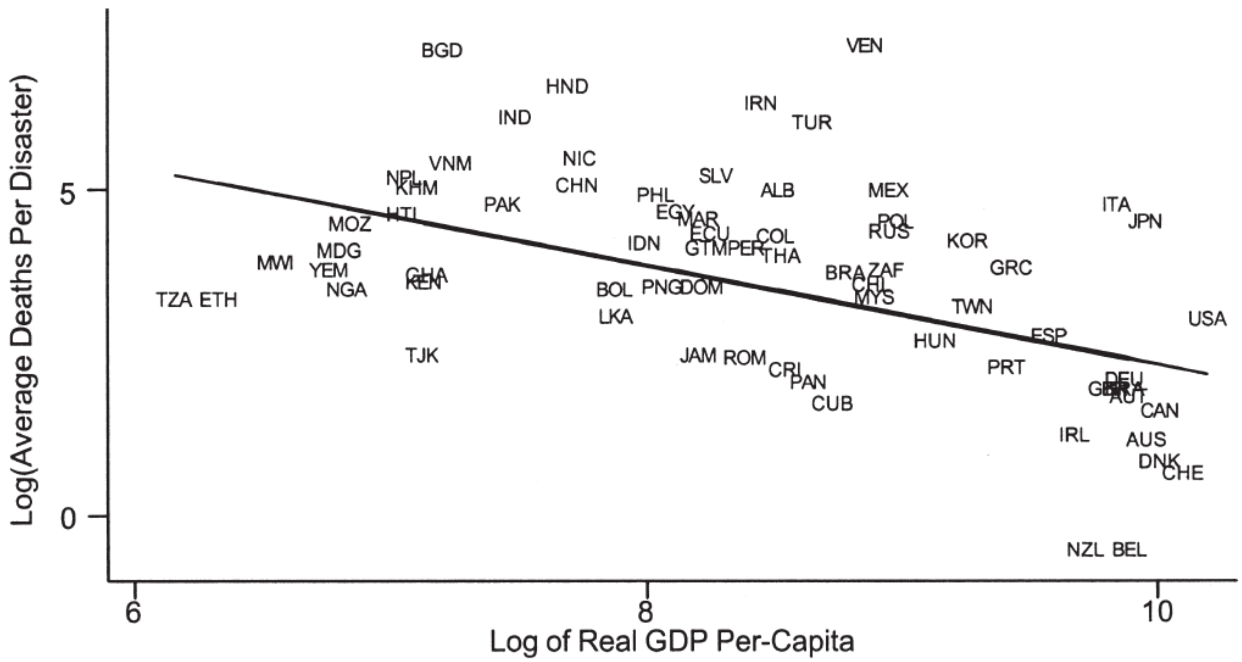
Study	Disaster Type	Geography and Time Period	Variables	Results
Choi and Fisher (2003)	Tropical Cyclones	United States, 1928-1998	Product of per capita real wealth index and population index	1% increase in either wealth or population causes a 0.38% increase in annual real losses
Schmidt et al (2009b)	Tropical Cyclones	United States, 1950-2005	Wind speed and capital stock	1% increase in capital stock causes a 0.441% or 0.515% increase in losses per storm [based on two different models]
Mendelsohn et al (2011)	Tropical Cyclones	United States, 1960-2008	Intensity (measured using minimum pressure), income, population density	1% increase in income causes a 0.370% or 0.903% increase in damages; 1% increase in population density causes a 0.488% or 0.458% increase in damages [based on two different models; coefficients are not statistically significant]
Zia (2012)	Tropical Cyclones	United States, 1900-2005	Housing density, hurricane intensity, wealth, agricultural land	1 additional house/square mile causes a 2.8% increase in losses; +1 billion in wealth causes a 0.02% increase in losses
Choi and Fisher (2003)	Floods	United States, 1928-1998	Product of per capita real wealth index and population index	1% increase in either wealth or population causes a 0.78% increase in annual real losses
Choi and Fisher (2003)	Severe Weather	Mid-Atlantic, 1951-1997	Product of per capita real wealth index and population index	1% increase in either wealth or population causes a 1.43% increase in annual real storm losses
Toya and Skidmore (2007)	Earthquake, Flood, Volcano, Wind, & Wave	World, time period unclear	Real per capita GDP	1% increase in wealth causes a 0.499% increase in damages; 1% increase in population causes a 0.501% increase in damages

4.2.2 Determinants of Mortality

In addition to analyzing the determinants of economic losses from natural disasters, a number of studies have also studied determinants of mortality. These studies tend to find a strong cross-sectional relationship in which higher levels of development lead to lower mortality from extreme weather (and disasters more broadly).

For example, Kahn (2005) uses a balanced panel of 73 countries from 1980 to 2002 to study the cross-sectional relationship between development and mortality from disasters. Figure 2 shows raw data from the study. In the figure, the x-axis represents the log of per-capita GDP, and the y-axis represents average deaths per disaster. The figure shows that even in the raw data, there is a clear negative relationship between a country's wealth and its mortality from disasters. Furthermore, using zero-inflated binomial regressions, the study finds that per capita GDP has a strong, statistically significant negative effect on disaster mortality. The coefficients imply that for every $1,000 of additional per capita income, a nation's average annual disaster deaths decrease by 17.6% for windstorms, 10.6% for floods, and 6.1% for landslides.

Figure 2: Natural Disaster Deaths Versus Per Capita GDP, by Country



Source: Reproduced from Figure 2 of Kahn (2005).

4.3 Parameter Estimates

This section summarizes estimated values of the elasticity of damages with respect to income and population. We generate these results by combining relevant estimates drawn from the regression-based studies listed in Table 6. This requires converting all regression coefficients into elasticities.

To illustrate this standardization procedure, consider the regression results from Toya and Skidmore (2007), which imply that the elasticity of damages per GDP with respect to GDP per capita is -0.501. The regression specification which the authors use to estimate this parameter can be summarized as:

$$\ln\left(\frac{D_{it}}{Y_{it}}\right) = \alpha_i + \phi \cdot \ln\left(\frac{Y_{it}}{P_{it}}\right)$$

Solving for total damages D_{it} as a function of GDP Y_{it} and population P_{it} gives the following equation:

$$D_{it} = \exp(\alpha_i) \cdot Y_{it}^{\phi+1} \cdot P_{it}^{-\phi}$$

This equation shows that the elasticity of damages with respect to GDP is $\phi + 1$, and the elasticity of damages with respect to population is $-\phi$. For a value of ϕ of -0.501, the results are reasonable, with damage elasticities of about 0.5 for both GDP and population. More generally, however, it is not clear why the functional form should impose a tradeoff between the elasticities with respect to GDP and population. Similar issues arise in a number of other studies. For example, Choi and Fisher (2003) use a specification that implies that damage elasticities with respect to GDP and population are equal. These issues with specification are important, because previous IAM work has essentially adopted the specifications present in the literature. For example, Narita, Tol, and Anthoff (2009) and Narita, Tol, and Anthoff (2010) both use specifications based on the Toya and Skidmore (2007) framework.

Our analysis draws on results from three studies: Choi and Fisher (2003), Toya and Skidmore (2007), and Mendelsohn et al (2011). Each of these studies provides one or more regression parameters that can be used to derive the elasticity of damages with respect to population or GDP. To combine multiple results from different studies, we model each elasticity using a t-distribution. For simplicity, we do not weight values based on statistical precision, but instead treat all observations equally.

Table 7 reports the results of this analysis. The table shows that across the estimates in our sample, the mean elasticity of damages with respect to GDP (or income) is 0.73, and the mean elasticity with respect to population is 0.67. We note that these estimates are subject to several limitations. First, these estimates are based on only a few studies. Second, the confidence intervals on these estimates are large. Third, the t-distribution may not provide the best fit for this data.

Table 7: Parameters Representing the Effect of Socioeconomic Growth on Extreme Weather Losses

	Parameter Description	Mean Value	Standard Deviation	Range		Parametric 95% Confidence Interval		N
				Minimum	Maximum	Lower Bound	Upper Bound	
λ	Exponent for income growth ratio	0.73	0.41	0.37	1.43	-0.316	1.78	6
π	Exponent for population growth ratio	0.67	0.40	0.38	1.43	-0.34	1.69	6

Notes: Some studies included in the analysis consider the elasticity of annual damages due to tropical cyclones with respect to income and population growth while others estimate the elasticity of damages per storm.

5 The Effects of Climate Change on Extreme Weather Losses

The previous two sections of this document review recent research on the magnitude and socioeconomic determinants of historical extreme weather losses. In this section, we review evidence on how climate change is likely to influence future extreme weather losses.

This literature on this subject has grown rapidly in recent years, particularly for tropical cyclones, extratropical cyclones, and floods. However, the core objective of predicting the impacts of climate change remains highly challenging. The physical science chain that connects climate change to extreme weather losses is complicated and poorly understood. Additionally, modeling the effects of climate change is made more difficult by the fact that most general circulation models (GCMs) of the earth's atmosphere lack the spatial resolution necessary to model the formation of even very large storm systems. To compound these modeling challenges, there is not yet a sufficiently long historical record to test the predictions that emerge from current models. For example, although some studies have found trends in hurricane intensity and power dissipation over the last several decades (IPCC, 2012), other studies are skeptical that it will ever be possible to use empirical data to measure the effects of climate change on tropical cyclone damages. To illustrate, based on an ensemble of 18 climate change hurricane damage models, Crompton, Pielke, and McAneney (2011) estimate that it will take between 120 and 550 years for a detectable signal to emerge from the noise.

Because of these and other limitations, our review of this literature requires two important qualifications. First, we acknowledge that there is considerable uncertainty about how climate change is likely to influence future damages. For some types of events, such as tropical cyclones and inland flooding, this uncertainty is highlighted by disagreement between the predictions from different studies. For other types of extreme weather, such as wildfires and landslides/avalanches, the uncertainty is evident in the scarcity of relevant studies.

Second, we acknowledge that our review makes important simplifying assumptions about the relationship between climate change and extreme weather. Much of the literature on climate change and extreme weather is not well-suited for incorporation into an integrated assessment model framework. For example, many of the best studies of tropical cyclones use complex methodologies that rely on information such as sea-surface temperature differentials. Our goal is to develop a set of parameters that can be used in integrated assessment models, which require simple functional forms and typically are not capable of detailed atmospheric modelling. Thus, we focus on describing high-level predictions of the climate change-damage relationship for large geographic areas, in which we represent the change in future damages as simple function of the change in surface atmospheric temperature. This is certainly a simplification, but the alterative—attempting to build a meta-model that incorporates detailed geographic and climate scenario information—is not yet practical, given the current state of the literature.

The remainder of this section is organized by type of extreme weather event, with separate subsections for tropical cyclones, extratropical cyclones, inland floods, wildfires, small-scale storm-related phenomena, and landslides and avalanches. In each subsection, we begin by providing a short overview of the causal pathway that connects greenhouse gas emissions to changes in future extreme weather damages, via changes in climate (air temperature, sea surface temperature) and their effects on changes in extreme weather patterns (frequency, intensity, geographic distribution). Next, we review the modeling techniques that are used to make projections about future losses. Finally, each subsection ends with a summary of existing empirical predictions about future extreme weather losses under climate change.

As a supplement to the material covered here, we have also assembled an appendix for each type of disaster. In each appendix, we present EM-DAT data on the historical damages by detailed region, summarize key results from the IPCC's report on climate change and extreme weather, and provide a table that summarizes the methodologies and results from studies that project future damages. The appendices are located at the end of this document.

5.1 Tropical Cyclones

This section reviews recent evidence on the impacts of climate change on tropical cyclone damages. In Section 5.1.1, we discuss the physical mechanisms through which changes in the climate could affect tropical cyclones. Next, in Section 5.1.2, we explain the methodologies that have been used in studies that project damages due tropical cyclones. Finally, in Section 5.1.3, we summarize empirical projections of future tropical cyclone losses.

5.1.1 Climate Change and Tropical Cyclones

Tropical cyclones cause damage through a number of mechanisms, including strong winds, heavy rain, flooding, and storm surges (Burton and Hicks, 2005; Emanuel, 2011; Pielke et al, 2008; Ranger and Niehörster, 2011). Furthermore, the formation and evolution of tropical cyclones depends on a number of variables, including absolute sea surface temperatures (SST), sea surface temperature gradients, atmospheric instability, and vertical wind shear (Dare and McBride 2011; Bender et al 2010; Knutson et al 2010). Climate change could affect tropical cyclones via a number of these pathways.

For example, one mechanism through which climate change could influence tropical cyclone formation is via an increase in sea surface temperatures. Some research has suggested that SST and the potential intensity of storms are strongly correlated, implying that climate change would increase the relative frequency with which intense cyclones occur. However, recent research shows that potential intensity may in fact be more related to SST gradients between tropical and non-tropical areas. Since SST gradients are not predicted to be affected by climate change, this research implies that climate change will have little effect on tropical cyclone potential intensity (IPCC, 2012, p. 119, 158-163).

Another mechanism through which climate change could affect tropical cyclones is via an increase in atmospheric water vapor. Since water vapor is strongly related to heavy precipitation, it is possible that climate change will cause an increase in heavy precipitation associated with tropical cyclones (IPCC, 2012, p. 162).

Climate change may also indirectly influence the destructiveness of tropical cyclones through an increase in sea levels. With higher average sea levels, the impacts of storm surges will increase, even if there is no change in storm frequency, wind speed, or other characteristics (IPCC, 2012, p. 158).

Finally, some aspects of climate change may lead to a decrease in tropical cyclone frequency. Potential mechanisms for negative effects include an increase in vertical wind shear, a reduction in the upward movement of air masses associated with atmospheric circulation in the tropics, and an increase in the amount of water vapor needed to saturate air in the middle troposphere (IPCC, 2012, p. 162). All of these changes would reduce the potential energy available to storms, by siphoning away heat and moisture, or by making it more difficult for water vapor to condense and release heat energy.

Overall, the IPCC projects that worldwide, the frequency of tropical cyclones will decrease or remain constant, while near-storm precipitation will rise. However, changes will vary across basins, with some basins seeing a rise in the mean maximum wind speed for storms and some basins experiencing a rise in frequency of the most intense storms (IPCC, 2012).

5.1.2 Methodologies for Modeling Tropical Cyclone Losses under Climate Change

This section discusses the scientific and economic methodologies used to forecast damages from tropical cyclones under future climate change. Typically, models that predict future damages include two components: one module that predicts how climate change will affect the frequency and intensity of future tropical cyclones, and a second module that estimates how those predicted changes will translate into economic damages. We discuss these issues separately in the subsections below.

Modeling Changes in Future Weather

Projecting how climate change will affect the incidence of tropical cyclones is a difficult modeling process. Most studies start by forecasting how changes in greenhouse gas emissions will affect future climate. These predictions are usually based on general circulation models (GCMs) that predict how changes in forcing under different emissions scenarios will affect atmospheric and sea surface temperatures.

The next step is then to model how changes in future climate will affect tropical cyclones. Since tropical cyclones are complex events whose formation is influenced by a number of mechanisms (Bender et al 2010; Dare and McBride 2011; IPCC, 2012; Knutson et al 2010), making credible forecasts requires fairly complicated modeling approaches (Bender et al, 2010; Emanuel, 2011; Neumann et al, 2014). Several main methodologies have emerged from the literature.

First, some studies explicitly model tropical cyclones within a GCM framework (Emanuel, 2011). These models forecast changes over the globe, with relatively low resolution. These models have the strength of allowing for feedbacks between tropical cyclone formation and global atmospheric conditions—e.g., through dissipation of heat energy from the tropics to more temperate latitudes. However, because tropical cyclones tend to be regional or local phenomena, some authors have questioned whether current models have the spatial granularity necessary to predict cyclone formation and evolution.

A second common approach is to generate forecasts using dynamical downscaling. This process involves taking low-resolution predicted changes in atmospheric conditions from a GCM and using them as inputs for a higher-resolution regional or local atmospheric model (Emanuel, 2011). For example, Bender et al (2010) uses a dynamic downscaling approach to predict future U.S. hurricane patterns under the IPCC's A1b emissions scenario. The study begins with a set of GCM predictions taken from the Coupled Model Intercomparison Project 3 (CMIP3). The authors then use the ZETAC model, which has 18-km resolution, to downscale the GCM climate predictions to finer resolution. This downscaling process allows the authors to simulate important atmospheric conditions that affect tropical cyclone formation, including changes in SST, potential intensity, and wind shear. Finally, the authors use these downscaled atmospheric variables as inputs to the Geophysical Fluid Dynamics Laboratory (GFDL) hurricane model, when then generates a series of simulated storm tracks. The outputs from the model can be used to characterize the frequency, intensity, and geographic distribution of hurricanes under future climatic conditions.

A third approach is statistical downscaling. This process involves using the observed historical relationships between the large-scale variables that are outputs of the GCMs and local parameters to project changes in tropical cyclones (Emanuel, 2011). Finally, some studies use simplified approaches that avoid explicit atmospheric modeling. In some cases, authors use predictions from previous modeling work as inputs for their own economic calculations (ABI, 2009; Neumann et al, 2014; Ranger and Niehorster, 2011; Schmidt et al, 2009). For example, Neumann et al (2014) uses simulated storm tracks from Emanuel et al (2008), and ABI (2009) uses the mean estimate (over seven models) of changes in North Indian Ocean wind speed from Emanuel et al (2008). In other cases, studies use non-model-based techniques such as expert elicitation (ECAWG, 2009; Pielke, 2007) or estimation of a multiplier (e.g. an increase in intensity of 50%) (Fankhauser, 1995). These studies often seek to understand how damages would respond to a specific change in the frequency or intensity of tropical cyclones, not necessarily connected to particular climate change scenario.

In addition to modeling the effects of climate change on tropical cyclone formation, some authors have considered the impact of tropical cyclones on storm surges. For example, Neumann et al (2014) draws on sea level rise outputs from a GCM and wind field output from a simulation of tropical cyclone storm tracks based on Emanuel et al (2008). By combining these results using NOAA's Sea, Lake, and Overland Surge from Hurricanes (SLOSH) model, the authors are able to estimate location-specific cumulative distribution functions for future storm surge height due to tropical cyclones.

One issue that frequently emerges the literature on tropical cyclones—and on extreme weather more broadly—is how to test and validate model predictions. One approach that is common is to test whether the model is able to simulate tropical cyclone patterns correctly under known historical conditions. For example, Bender et al (2010) test the GFDL hurricane models using historical data and find that while the preferred model correctly predicts increased intensity during a more active cyclone period, it does not accurately predict the magnitude of this change. The authors speculate that future models, with increased horizontal resolution and explicit consideration of convection, may be better able to reproduce historical conditions. This iterative approach to model development is common, but raises the possibility that future models will be guided by previous validation exercises—implying that future tests would need to be based on historical data from different locations or time periods.

Modeling Economic Losses

After projecting how tropical cyclone patterns will be affected by climate change, studies then must translate these changes in weather patterns into predicted changes in economic losses. To model future economic losses from simulated storms, studies typically rely on a damage function derived from the historical relationship between storm characteristics to losses. As discussed in Section 3, there are several different approaches and potential sources of data that could be used to estimate this relationship.

The most common approach in the literature is model damages from simulated storms based on the historical relationship between losses and maximum wind speed (Hallegate, 2007; Narita, Tol, and Anthoff, 2009; Nordhaus, 2010). Although many studies use this approach, there is considerable disagreement about the exact functional form of the relationship, with studies using semi-elasticities that range from a 2.8% increase in losses per knot (Schmidt et al, 2008b) to a 9.4% increase in losses per knot (Nordhaus, 2010). One variation on this approach is to model damages as a function of Saffir-Simpson hurricane category, and then to estimate future damages by applying these values to the estimated change in number of storms of each category (Bender et al, 2010)

Some studies also use more complex damage functions that take into account factors other than wind speed. For example, Emanuel (2011) models damages as a function of both wind speed and explicit storm tracks. The study uses historical data on insured damages in 100 zones across the U.S. East and Gulf Coasts to develop a model of how losses depend on the locations hit by a storm. The author then uses this historical relationship to predict damages from simulated future storm tracks. Similarly, Mendelsohn, Emanuel, and Chonabayashi (2011) use a regression-based damage function that models damages as a function of minimum barometric pressure, maximum wind speed, and location at landfall. Finally, several studies measure the broader economic consequences of tropical cyclones by embedding storm loss models within integrated assessment model frameworks (e.g., Narita, Tol, and Anthoff, 2009; Roson et al, 2006).

In addition to projecting how climate-driven changes in storm characteristics will affect losses, some studies also account for the fact that future storm losses will be higher due to socioeconomic growth. In these studies, authors typically project future losses under both climate change and socioeconomic growth, and then compare that to losses with socioeconomic growth but without climate change. To account for socioeconomic growth, studies typically use simple adjustments based on predicted changes in population or GDP, combined with estimates of the elasticity of storm damages with respect to those parameters (Mendelsohn, Emanuel, and Chonabayashi, 2011; Narita, Tol, and Anthoff, 2009; Stanton & Ackerman, 2007). A few studies consider the possibility of adaptation (e.g., Neumann et al, 2014)—we discuss these studies in greater detail in Section 6.2.

One other methodological choice that is important is the type of damages considered by each study, e.g., insured losses, direct losses, or value of lives lost. For example, Emanuel (2011) relies on a dataset of insured values from Risk Management Solutions, and therefore is only projecting changes in insured losses. In contrast, ABI (2005) projects total direct damages from future cyclones by inflating AIR Worldwide insurance estimates based the historical percentage of total damages that are insured.

Although most tropical cyclone studies focus on predicting future economic losses, a few consider other types of endpoints, such as power generation. For example, Esteban et al (2012) consider the implications of future tropical cyclones in Japan for the cost-effectiveness of installing green energy generation. Similarly, Hong and Möller (2012) evaluate the effects (both negative and positive) of future tropical cyclones on offshore wind farms in China. Finally, Bjarnadottir et al (2013) analyzes the impact of tropical cyclones on the failure probability for electricity distribution poles. These papers use context-specific methodologies that are quite different from the general approaches described above.

5.1.3 Projections of Tropical Cyclone Losses under Climate Change

This section provides a review of recent empirical estimates of how tropical cyclone damages are likely to change under future climatic conditions. Table 8 lists all studies that we have been able to identify on this topic. Each of these studies projects damages under future climatic conditions. As the table shows, these studies consider a diverse set of climate change scenarios, and focus on a wide range of geographies.

Because of the variation in these studies, including in the methodological approaches they take and the format in which they report results, combining projections from different studies requires standardizing estimates and converting to consistent units. To address this issue, we summarize the results from a recent meta-analysis of this literature, Ranson et al (2014). In that study, the authors normalized each loss prediction from each study as a percent change in damages per degree Celsius of warming. The authors then calculated a probability distribution that captures the range of estimates across different studies. Note that Ranson et al (2014) excludes some studies from Table 8, either because the studies were published after the meta-analysis was completed, or because they do not estimate the change in mean annual losses (e.g., several studies report results in terms of changes in return periods).

Figure 3 summarizes the normalized predictions from each study included in the meta-analysis. The figure shows that there is considerable variation across estimates, with the predicted change in losses ranging from -20% to +70% per degree Celsius. The average study predicts approximately a 15% increase in damages in the North Atlantic, a 6% increase in damages in the Western North Pacific, and a 14% increase in other/multiple ocean basins.

In the parametric model presented in Section 2, we assume that the effect of climate change on tropical cyclone costs $C_i(\Delta T_t)$ can be expressed using an exponential functional form:

$$C_i(\Delta T_t) = (1 + \tau_i)^{\Delta T_t}$$

The regression results from Ranson et al (2014) assume that $1 + \tau_i$ has a lognormal distribution:

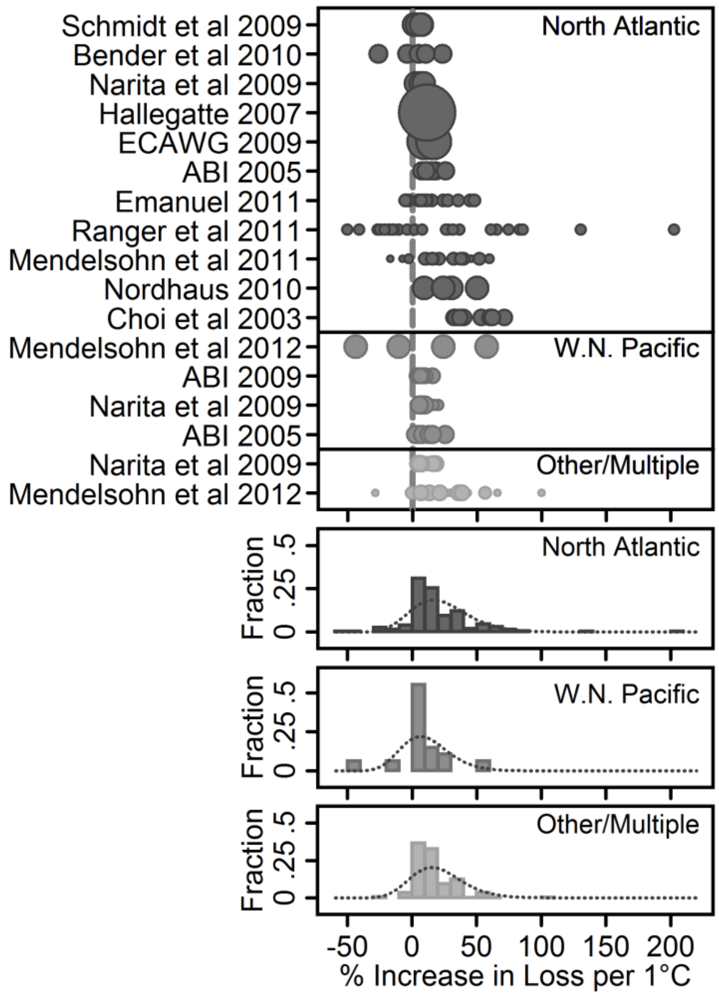
$$\ln(1 + \tau_i) \sim N(\mu_i, \sigma_i)$$

The study estimates that $\mu_i = 0.154$ and $\sigma_i = 0.182$ in the North Atlantic, $\mu_i = 0.063$ and $\sigma_i = 0.168$ in in the Western North Pacific, and $\mu_i = 0.144$ and $\sigma_i = 0.167$ in other/multiple ocean basins.

Table 8: Studies of Tropical Cyclone Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
ABI (2009)	China	"time independent"	+2°C, +4°C, +6°C; wind: -.5%, +3.7, +8%
Bender et al (2010)	U.S.	1980-2006	A1B
Emanuel (2011)	U.S. East/Gulf	2000-2100	A1B
Esteban et al (2010)	Japan	2085	+1% annual CO_2 (SST: +0.8°C to 2.4°C)
Webersik et al (2010)	Japan	2085	+1% annual CO_2
Esteban et al (2010)	Japan	2085	+1% annual CO_2
Raible et al (2012)	U.S.	2069-2100; 2080-99	A2; A1B
Hallegate (2007)	11 U.S. regions	Not specified	10% increase in potential intensity
Mendelsohn et al (2011)	U.S.	2100	A1B
Mendelsohn et al (2012)	World regions	2100	A1B
ABI (2005)	U.S., Japan	2020-2099	A1T, A1F1, A2, B1, B2, 550, IS92a
Ackerman et al, 2008	U.S.	2025-2100	A2
Bouwer et al (2011)	U.S.	Not specified	2.5°C rise in SST
Choi and Fisher (2003)	U.S.	Not specified	+13.5% and +21.5% precipitation (2x CO_2)
ECAWG (2009)	South Florida	2030	+3%WS/+.08m SLR; +5%WS/+.24m SLR
ECLAC (2011)	Bahamas	2011-2051	SLR only?
Fankhauser (1995)	World	Not specified	Doubling of CO_2
Moore et al (2010)	Barbados	2071-2100	Five hurricane probability scenarios
Nordhaus (2010)	U.S.	Not specified	Equilibrium doubling of CO_2-e levels
Pielke (2007)	U.S.	2050	CO2 concentration 550ppm in 2050
Pielke et al (2000)	World	2050	A1, A2, B1, B2
Ranger et al (2011)	Florida	2020 and 2090	A1B
Schmidt et al (2009a)	U.S.	2015, 2050	A1
Stanton et al (2007)	Florida	2025-2100	A2, Rapid Stabilization
Narita et al (2009)	World regions	2100	EMF 14 standardized scenario
Neumann et al (2014)	U.S.	2100	3 emissions scenarios
Esteban et al (2009)	Taiwan	2085	Linear 1% annual CO2 increase
Hsiang and Jina (2014)	World countries	2090	A1B
Peduzzi et al (2012)	World	2030	Based on Knutson et al (2010)
Emanuel et al (2012)	U.S. East/Gulf	Not specified	Not specified
Seo (2014)	S. Hemisphere	2100	A1B
Bjarnadottir et al (2014)	3 U.S. counties	Not specified	9 wind speed change scenarios
Bjarnadottir et al (2011)	Florida	Not specified	0-10% wind speed change
Chavas et al (2013)	U.S.	2081-2100	A1B
Irish et al (2010)	U.S. Gulf	2030s, 2080s	B1, A1B, A1F1
Esteban et al (2014)	Vietnam	2050-2100	SLR 0.15-1.35m
Toba (2009)	CARICOM	2080	A1B
Roson et al (2006)	World, by region	2050	1 to 1.75 deg C warming by 2050

Figure 3: Projected Changes in Tropical Cyclone Damages Due to Climate Change



Notes: Each point in the scatterplot in top part of the figure represents a unique estimate of the treatment effect of surface air temperature on losses, based on a particular study, methodology, geography, and temperature change. The marker size represents the weight assigned to the treatment effect, and reflects both the baseline damages in that geography as well as the inverse of the number of estimates provided by the study. Weights are calculated separately for each of the three basins. The histograms in the bottom part of the figure show the distribution of estimates in each basin, along with a dotted line that represents a fitted log-normal distribution. Source: Ranson et al, 2014

5.2 Extratropical Cyclones

This section reviews recent evidence on the impacts of climate change on extratropical cyclone damages. In Section 5.2.1, we discuss the physical mechanisms through which changes in the climate could affect extratropical cyclones. Next, in Section 5.2.2, we explain the methodologies that have been used in studies that project damages due extratropical cyclones. Finally, in Section 5.2.3, we summarize empirical projections of future extratropical cyclone losses.

5.2.1 Climate Change and Extratropical Cyclones

Extratropical cyclones tend to occur over mid-latitude ocean basins located near the upper-tropospheric jet streams. These storms typically form in areas where the atmosphere is unstable, due, for example, to temperature gradients between large air masses. They can gain energy via a number of mechanisms, including latent heat release (heat energy released when atmospheric water vapor condenses and falls as rain) (IPCC, 2012, p. 163). Extratropical cyclones can also cause damages through several different mechanisms, including strong winds and storm surges. In some cases, extratropical cyclones may also be associated with heavy rain or snow, which in turn may lead to further economic impacts (Donat et al, 2011; ECAWG, 2009; Mass & Dotson, 2010).

There are a number of pathways through which climate change could affect extratropical cyclones. For example, if climate change were to impact the pole-to-equator temperature gradients—at low or high altitudes—this could lead to a poleward shift in the atmospheric instabilities that generate extratropical cyclones. In addition, if climate change were to affect atmospheric moisture content, the precipitation intensity within extratropical cyclones could change, which in turn could affect latent heat release and cyclone intensity (IPCC, 2012, p. 163).

Overall, the IPCC projects that anthropogenic influences will result in a poleward shift in tracks from these storms. This conclusion is based on indirect evidence, as well as on recent empirical observations of an ongoing poleward shift in extratropical storm tracks (IPCC, 2012, p. 119). Although regional storm activity will likely be affected by climate change, the specific details of regional predictions should be interpreted with caution, due current models' inability to capture all aspects of the way that extratropical cyclones form and change (IPCC, 2012, p. 119, 164-165). Based on the IPCC's review, it is not clear whether climate change will actually affect the global intensity and frequency of extratropical cyclones, or is likely only to shift storm activity northward.

5.2.2 Methodologies for Modeling Extratropical Cyclone Losses under Climate Change

This section discusses the scientific and economic methodologies used to forecast damages from extratropical cyclones under future climate change. As with tropical cyclones, these models include two components: one module that predicts how climate change will affect the frequency and intensity of future extratropical cyclones, and a second module that estimates how those predicted changes will translate into economic damages.

Modeling Changes in Future Weather

The general methods used for modeling changes in extratropical cyclones are similar to those described for tropical cyclones (see Section 5.1.2). Studies first project the effects of greenhouse gas emissions on global and regional future climate, and then translate the resulting climatic changes into changes in extratropical cyclone activity. Many studies only model extratropical cyclones in the winter season, as the majority of storms occur during this period (Donate et al, 2011; Pinto et al 2012; Pinto et al, 2007).

As with tropical cyclones, some studies estimate changes in extratropical cyclone activity directly from GCM predictions for daily maximum wind speeds. For example, Leckebusch et al (2007) argue that while using a RCM could provide more geographic detail, the results of the GCMs are sufficient for determining a climate signal. Pinto et al (2007) also explicitly model changes in extratropical cyclones using GCM outputs, but rely on an ensemble of simulations.

Other studies rely on dynamical or statistical downscaling of GCM results (Donat et al, 2011; Schwierz et al 2010). For example, Held et al (2013) downscales three ways: using dynamical downscaling, statistical downscaling, and using a hybrid model (similar to Pinto et al, 2010). For the hybrid method, Held et al (2013) dynamically downscales GCM predictions to generate changes in regional frequencies of weather types, and then uses statistical distributions of climate variables.

Again, as with tropical cyclones, a number of studies also use simplifying approaches for predicting changes in extratropical cyclones. For example, ABI (2005) relies on the results of Leckebusch and Ulbrich (2004), and assumes that climate change results in a 20 percent increase in intensity of the 20-year storm.

Modeling Economic Losses

Once a study generates predictions about future extratropical cyclones patterns, these changes must be converted into economic damages. Unlike the literature on tropical cyclones, which exhibits a range of economic loss modeling approaches, the nearly all studies of extratropical cyclones rely on a linear regression model that predicts damages based on the cube of normalized wind speeds above a 98th percentile threshold value. A subset of these studies run the damage model twice: once calculating the 98th percentile threshold given future climate to account for local adaptation, and once holding the threshold value constant at present day values, assuming no adaptation. Some of these models also take into consideration a variable for population density, which acts as a proxy for insured values (assuming implicitly that insured values are proportional to population density) (Donat et al, 2011; Leckebusch et al, 2007; Pinto et al, 2007; Pinto et al, 2010; Pinto et al, 2012; Held et al, 2013). A few studies also use other functional forms to represent the relationship between damages and wind speed (Held et al, 2013; Schwierz et al, 2010). Narita et al (2010) is an outlier in that it models damages directly the frequency of storm occurrence. Finally, ABI (2009) and ABI (2005) estimate damages using a proprietary AIRS Worldwide insurance damage model.

5.2.3 Projections of Extratropical Cyclone Losses under Climate Change

This section reviews recent empirical estimates of how extratropical cyclone damages are likely to change under future climatic conditions. Table 9 lists all studies that we have been able to identify on this topic. As the table illustrates, most research on extratropical cyclones has focused on Europe, with only a few studies that have considered other geographic locations.

To summarize the empirical results from this literature, we draw on a recent meta-analysis by Ranson et al (2014). In that study, the authors normalized each projection from each study in terms of a predicted change in losses per degree Celsius of atmospheric warming. Note that Ranson et al (2014) excludes some studies from Table 9, either because the studies were published after the meta-analysis was completed, or because they do not estimate the change in mean annual losses (e.g., several studies report results in terms of changes in return periods).

Figure 4 summarizes the key results from the meta-analysis. The figure shows that across the eight studies included in the meta-analysis, the average predicted increase in wind storm losses in Europe is +8% per degree Celsius of warming. To incorporate these results into our report, we assume that the effect of climate change on extratropical cyclone costs $C_i(\Delta T_t)$ can be modeled as:

$$C_i(\Delta T_t) = (1 + \tau_i)^{\Delta T_t}$$

The regression results from Ranson et al (2014) assume that $1 + \tau_i$ has a lognormal distribution:

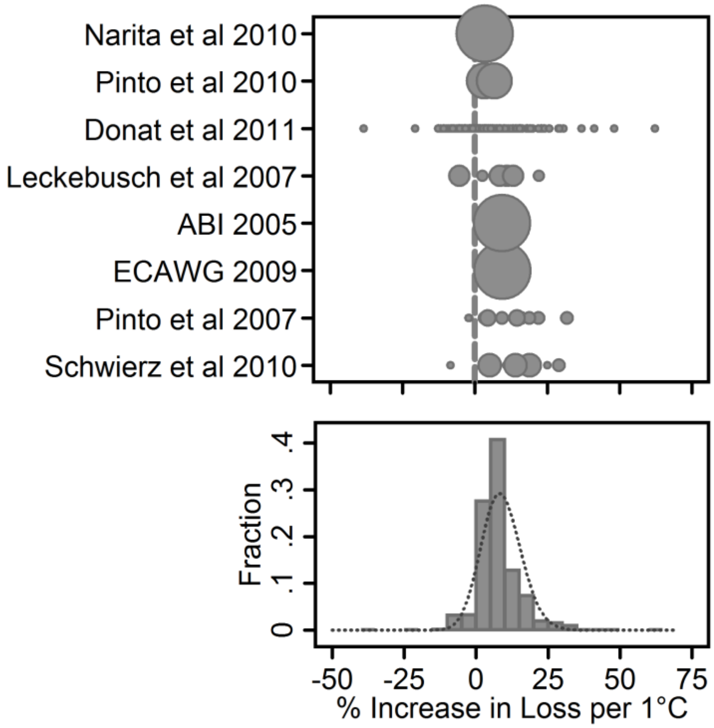
$$\ln(1 + \tau_i) \sim N(\mu_i, \sigma_i)$$

The study estimates that $\mu_i = 0.078$ and $\sigma_i = 0.063$ for extratropical cyclones in Europe.

Table 9: Studies of Extratropical Cyclone Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
ABI (2009)	UK	"time independent"	storm track shift of -1.45°, -4.4°, -7.3°
Narita et al (2010)	16 world regions	2100	EMF 14 standardized scenario
Leckebusch et al (2007)	UK & Germany	2070-99, 2060-2100	A2 and IS92a
Pinto et al (2007)	Europe	2060-2100	A1B and A2
Pinto et al (2010)	Germany	2060-2100	A1B and A2
Pinto et al (2012)	Europe	2060-2100	B1,A1B, and A2
Held et al (2013)	Germany	2070, 2100	A1B
Donat et al (2011)	Europe	2021-50, 2071-2100	A1B
Schwierz et al (2010)	Europe	2071-2100	A2
ABI (2005)	Europe	Not specified	A2
Roson et al (2006)	World, by region	2050	1 to 1.75 deg C warming by 2050
Della-Marta et al (2010)	Europe	Not specified	ECMWF climate forecasts
Heck et al (2006)	Europe	2071-2100	A2
Karremann et al (2014)	Europe	2060-2100	A1B
Karremann (2015)	Europe	2060-2100	B1, A1B, A2
Hanson et al (2004)	UK	2070-2099	A2, B2
Dorland et al (1999)	Netherlands	2015	0-10% wind intensity increase

Figure 4: Projected Changes in Extratropical Cyclone Losses Due to Climate Change



Notes: Each point in the scatterplot in top part of the figure represents a unique estimate of the treatment effect of surface air temperature on losses, based on a particular study, methodology, geography, and temperature change. The marker size represents the weight assigned to the treatment effect, and reflects both the baseline damages in that geography as well as the inverse of the number of estimates provided by the study. Weights are calculated separately for each of the three basins. The histograms in the bottom part of the figure show the distribution of estimates in each basin, along with a dotted line that represents a fitted log-normal distribution. Source: Ranson et al, 2014

5.3 Inland Flooding

This section reviews recent evidence on the impacts of climate change on damages from inland flooding. In Section 5.3.1, we discuss the physical mechanisms through which changes in the climate could affect inland flooding. Next, in Section 5.3.2, we explain the methodologies that have been used in studies that project damages due inland flooding. Finally, in Section 5.3.3, we summarize empirical projections of future inland flooding losses.

5.3.1 Climate Change and Inland Flooding

Inland floods can be divided into several categories, including floods along rivers ("fluvial" floods), floods that occur when heavy precipitation completely saturates the topsoil ("pluvial" floods – most common in urban areas), and floods related to glacial lakes. The primary natural causes of flooding are extreme precipitation, melting snow or ice melt, and blockages to water flow, such as those caused by landslides (IPCC, 2012, p. 175). Climate change could affect inland flooding via changes in either precipitation or surface air temperature. For example, increased flooding could result from an increase in long-lasting precipitation, from an increase in temperatures that leads to a rise in snow melt, or from changes in soil moisture content.

In selected regions where climate change is expected to cause increases in heavy precipitation, it is logical to expect that flooding may also increase. However, although there is good evidence that climate change will affect precipitation and snowmelt worldwide, the many factors that affect flooding make it difficult to make global projections about future impacts of climate change on flooding. Overall, IPCC does not draw strong conclusions about whether anthropogenic influences will affect inland flooding via changes in heavy precipitation. Similarly, although the IPCC indicates that snowmelt-fed and glacier-fed rivers will probably experience earlier spring peak flows, there is little evidence that this will impact the frequency or intensity of flooding (IPCC, 2012, p. 175-178). Finally, due to a lack of existing literature, the IPCC draws no conclusions about pluvial floods.

5.3.2 Methodologies for Modeling Inland Flooding Losses under Climate Change

This section discusses the scientific and economic methodologies used to forecast damages from inland flooding under future climate change. These models typically include two components: one for predicting changes in future flooding probabilities, and one for estimating the economic damages resulting from the predicted changes in flooding.

Modeling Changes in Future Inland Floods

To estimate the effects of climate change on future flood probabilities, most studies use a two-step modeling approach. The first step in these models is to use downscaled GCM predictions to generate estimates of future precipitation patterns in the study region. For estimating flood probabilities, this requires estimating the probability of extreme or long-lasting precipitation events. Studies use different methods to describe extreme precipitation, including 24-hour precipitation events (CLIMB, 2013; Preston, 2013), 10-day precipitation sums (Bouwer et al, 2010), and monthly rainfall sums (Campbell-Lendrum et al, 2003). Because extreme precipitation probabilities are difficult to estimate, different GCMs often make significantly different predictions about the probability of heavy precipitation events under a particular climate scenario (Campbell-Lendrum et al, 2003).

The second step in these models is to use predicted changes in precipitation to estimate how future flood frequency will change. Inland floods are typically described using “return periods”, which represent the average number of years between events of a particular magnitude. For example, a 100-year flood is the inundation depth that has a 1% chance of occurring in given year. A 200-year flood has a 0.5% change of occurring each year, and is more damaging than a 100-year flood. Predicting the effect of climate on flooding requires using predicted changes in precipitation to adjust current topography-based probabilities of flooding, to estimate how the return period of a flood of a given severity (inundation depth and extent) will change.

To make these predictions, some studies rely simply on the historical relationship between precipitation and flooding in a particular area (Bouwer et al, 2010; Choi et al, 2003; Hall et al, 2005; Mokrech et al, 2008; Wobus, 2014). Others use more sophisticated hydrological models that account for rainfall runoff, local geology, or river flows (CLIMB, 2004; ABI, 2009; Dasgupta et al, 2010; Aerts et al, 2011; Hallegatte et al, 2010; Schreider et al, 2000). For example, ABI (2009) predicts future flooding in Great Britain by using a model that considers how topography, climate-induced precipitation, and soil type all affect total drainage from rainfall to the rivers. The study then applies a large-scale stochastic hydrological model to convert drainage to runoff across the entire river network.

Modeling Economic Losses

After developing estimates of how the spatial extent and depth of flooding are likely to change under future climatic conditions, studies must then estimate the damages that are likely to result from those changes. This process requires developing a damage function that relates flood severity to flood damages, and then applying this relationship to the predicted changes in flood patterns.

One way in which this process differs across studies is in the level of geographic resolution included in the model. Some studies estimate damages for relatively large geographic areas, while others use GIS techniques to estimate damages for very fine geographic pixels (Susnik 2014; CLIMB, 2004; Dasgupta, 2010; Campbell-Lendrum et al, 2003). In these studies, the flooding model estimates inundation depth and area, and the resulting 3D output is overlain with geospatial land-use data to calculate the total number of pixels or properties that fall into a particular depth category. Each pixel or property is then assigned a unit flood cost, based on factors such as the type of structure (residential buildings, office buildings, parking lots, infrastructure) or the number of residents who would be affected (Tezuka et al, 2014).

For example, several studies of flooding in the Netherlands use a region-specific “damage scanner” approach that uses the HIS-SSM model to estimate losses based on inundation depth and land use (Aerts et al, 2011; Bouwer et al, 2010; Te Linde et al, 2011). The model distinguishes between several different land use types and direct damage categories, including losses of buildings, infrastructure, agriculture, and building content. It also includes an adjustment for indirect losses, equal to five percent of total damages. This model illustrates the accuracy gains from using higher resolution geospatial data. In particular, when the model is used to simulate flooding scenarios at both 25m and 100m resolutions, the 100m resolution simulation tends to overestimate losses in urban areas, due to overestimating the area of high-density urban areas that are actually flooded (Bouwer 2009)

One important input into flooding models is the damage function that relates losses to inundation depth and property characteristics. To develop damage functions, most studies rely on the historical relationship between insurance claims and flood depth. Some studies also attempt to account for potential adaptation measures, such as levees, dykes, and flood-proofing of buildings (e.g., CLIMB, 2004)

5.3.3 Projections of Inland Flooding Losses under Climate Change

This section reviews recent empirical estimates of how inland flooding damages are likely to change under future climatic conditions. Table 10 summarizes key information about all studies we have identified on this topic. The majority of these studies focus on fluvial floods that are caused by long-lasting precipitation, which increases the river discharge, overflowing the banks. One study, however, projects future impacts from pluvial floods in Mumbai, where extreme precipitation events cause flooding because of poor urban drainage systems (Hallegatte, 2010).

Table 10: Studies of Inland Flooding Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
ABI, 2009	Great Britain	2035-2100	2°C global temperature rise
Aerts et al, 2011	Netherlands	2015-2100	1°C, 2°C, 4°C temperature rise
Bouwer et al, 2010	Netherlands	2040	G, W+ (KMNI)
Cambell-Lendrum, 2003	World	2030	IS92a, s750, s550
Cheng et al, 2012	Canada	2046-2100	IS92a, A2, B2
CLIMB, 2004	Boston, MA	2001-2100	1% increase annual CO_2
Choi et al, 2002	U.S.	not specified	Doubling of CO_2
Dasgupta et al, 2010	Bangladesh	2050	A2
Feyen et al, 2009	Europe	2071-2100	A2
Hall et al, 2005	UK	2080s	B1, B2, A2, A1F1
Hallegatte et al, 2010	Mumbai	2080s	A2
Mirza, 2002	Bangladesh	unclear	2°C, 4°C, 6°C temperature rise
Mokrech et al, 2008	England	2020-2050	A1, A2, B1, B2
Nakajima et al, 2014	Japan	2000-2050	CSIRO, GFDL, MIROC, MRI
Perrels et al, 2010	Finland	2005-2050	A1F1, A1T, A1B, A2, B1, B2
Schreider et al, 2000	Australia	2030, 2070	CO_2 doubled
Schuurman, 1995	Netherlands	2050	2°C global temperature rise
Te Linde et al, 2011	Europe	2030	A1B, 2°C temperature rise
You et al, 2001	China	1995-2100	2.5°C global temperature rise
Wobus et al, 2014	US	2100	CO_2 doubled
Ciscar et al, 2011	Europe	2071-2100	A2, B2
Zhou et al, 2012	Denmark	2100	A2
Tezuka et al, 2014	Japan	2050	A1B, B2, B1

To summarize the results from this varied collection of studies, we have standardized the results from selected studies following the methodology used in Ranson et al (2014). Figure 5 presents the results of this analysis. The figure shows that the predicted change in flood losses per degree of warming varies considerably across studies and geographies, including both large increases as well as moderate decreases.

Although Figure 5 does show results by continent, in our judgment the number of studies available for North America and Australia is not sufficient to develop region-specific estimates of the impacts of climate change on inland flooding. Instead, we estimate a single pooled model that includes studies covering all three regions. Following the general framework from Section 2, we assume that the effect of climate change on inland flooding costs $C_i(\Delta T_t)$ can be modeled as:

$$C_i(\Delta T_t) = (1 + \tau_i)^{\Delta T_t}$$

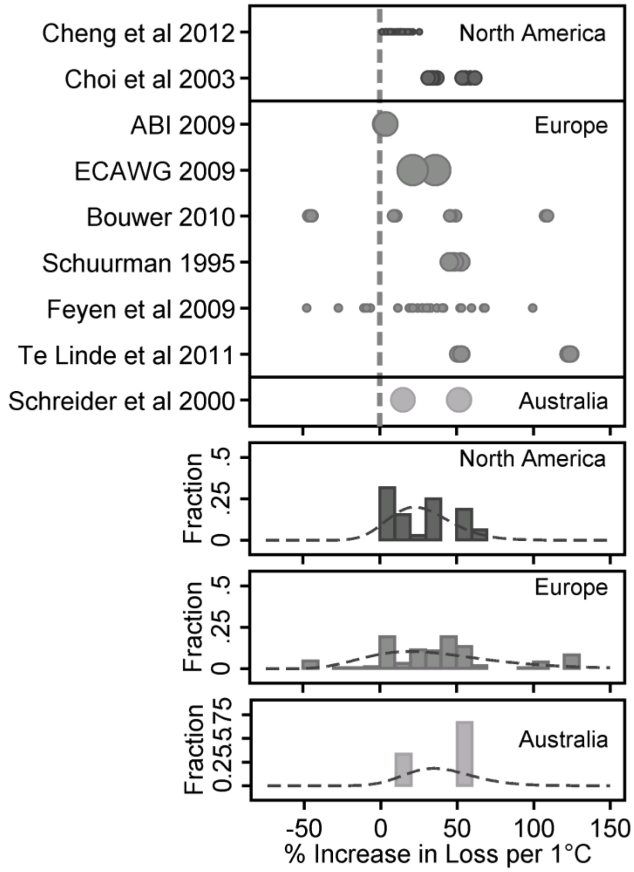
where $1 + \tau_i$ has a lognormal distribution:

$$\ln(1 + \tau_i) \sim N(\mu_i, \sigma_i)$$

Based on the sample of studies included in Figure 5, we estimate that $\mu_i = 0.274$ and $\sigma_i = 0.266$ for inland flooding in these three regions (Europe, North America, and Australia).

It is important to exercise caution in interpreting this pooled model and the other results shown in Figure 5. First, these results represent only part of the literature on inland flooding. Second, many of these studies focus on particular geographic areas or hydrological basins, and thus may not be representative of continental-level changes. This could be a concern if authors are more likely to simulate future losses for areas that are likely to have large impacts from climate change. Since the effects of climate change on inland floods are likely to be heterogeneous, making generalizations based on these studies requires fairly strong assumptions. We present these results here as an initial step towards developing a consensus damage function, but we have low overall confidence in the accuracy of our model parameters.

Figure 5: Projected Changes in Inland Flooding Damages Due to Climate Change



Notes: Each point in the scatterplot in top part of the figure represents a unique estimate of the treatment effect of surface air temperature on losses, based on a particular study, methodology, geography, and temperature change. The marker size represents the weight assigned to the treatment effect, and reflects the inverse of the number of estimates provided by the study. Weights are calculated separately for each of the three areas. The histograms in the bottom part of the figure show the distribution of estimates in each area, along with a dotted line that represents a fitted log-normal distribution.

5.4 Wildfires

This section reviews recent evidence on the impacts of climate change on wildfire damages. In Section 5.4.1, we discuss the physical mechanisms through which changes in the climate could affect wildfires. Next, in Section 5.4.2, we explain the methodologies that have been used in studies that project damages due wildfires. Finally, in Section 5.4.3, we summarize empirical projections of future wildfire losses.

5.4.1 Climate Change and Wildfires

There are a number of mechanisms through which climate change could influence wildfire risk. The occurrence of wildfires is driven by fuel availability (e.g., grass, brush), by weather conditions, and by ignition rates (e.g., due to lightning or human causes). Each of these individual mechanisms could be affected by a changing climate. Higher temperatures, for example, could increase the likelihood of ignition, and therefore lead to an increase in the frequency and geographic extent of wildfires. Changes in temperature and precipitation could affect plant growth, which in turn could affect fuel availability (Cary et al, 2012).

Based on these mechanisms, the IPCC states that there is some evidence to support predictions of an increase in wildfire risk in Southern Europe and parts of Australia and New Zealand (IPCC, 2014). Other studies have also projected increases in wildfire risk in areas of Australia, South America, the western United States, and Canada (IPCC, 2012, p. 252-261).

These predictions are supported by more general evidence that droughts will rise in duration and frequency in certain regions of the world (southern Europe, central North America, Central America, Mexico, northeast Brazil, and southern Africa) under climate change (IPCC, 2012, p. 119). Furthermore, some studies have found evidence that climate change may already be affecting wildfire patterns in the Western United States and Canada (Gillett et al, 2004; IPCC, 2012; Westerling et al, 2006; Westerling and Bryant, 2008). These studies argue that observed increases in wildfires over the last several decades are related to rises in temperature and earlier snowmelt, each of which has been identified as a potential result of anthropogenic climate change.

5.4.2 Methodologies for Modeling Wildfire Losses under Climate Change

This section discusses the scientific and economic methodologies used to forecast damages from wildfires under future climate change. While a number of studies have attempted to project future fire risk, we are only aware of a single study that projects future economic losses. As a result, our discussion primarily focuses on estimating the potential impacts of climate change on fire risk.

The goal of these studies is to use the outputs of global and regional climate models to predict changes in wildfire risk. In some cases, studies project whether future weather conditions will be more conducive to wildfires, but stop short of estimating actual changes in fire incidence. For example, Hennessy et al (2005) estimates changes in future "fire weather", based on calculating how the Forest Fire Danger Index and Grassland Fire Danger Index will change under future weather conditions. These indices are based on variables such as temperature, precipitation, relative humidity, and wind speed.

Other studies actually calculate probability distributions for wildfires under future conditions. For example, Fried et al (2004) generates future wildfire size distributions based on fire danger indices. Their model incorporates fire suppression protocols and is geographically explicit, modeling behavior for individual events based on fuel type, slope and weather. The authors point out that studies that predict only weather indices do not account for the skewed probability distribution of fire severity or the interaction between wildfires and suppression.

5.4.3 Projections of Wildfire Losses under Climate Change

As discussed above, a number of studies have estimated how climate change will affect future fire risks (e.g., Williams, Karoly, and Tapper, 2001). For instance, Cary (2002) and Hennessy et al (2005a) predict increased fire-weather risk and increases in frequency and area burned for regions of Australia. Fried et al (2004) finds mixed results in future projections for California. The study estimates an increase in fire spread rates in Amador and Santa Clara, but no change or a decline in Humboldt.

Despite this research on climate change and wildfire risk, we are aware of only a single study on the potential effects of climate change on damages from wildfires: Howard (2014). Table 12 summarizes key information about the scenario and geographic coverage this study. The study begins by using the average historical ratio between suppression costs and total costs to argue that total current costs of wildfires in the United States are likely to be $20 to $125 billion (based on federal, state, and local fire suppression costs of $2 to $2.5 billion per year). They argue that climate change will increase these costs by 50% by the year 2050, based on estimates of changes in burned area from studies in the literature. They then estimate global wildfire losses under climate change based on the assumption that the ratio between world GDP and world fire costs is equal to the ratio between U.S. GDP and U.S. fire costs. Overall, they predict that by the year 2050, climate change will cause additional wildfire damages of $10 to $62.5 billion in the United States, and $50 to $300 billion worldwide.

Howard (2014) relies on a number of strong assumptions, and the results should be interpreted with caution. However, the study does represent a first effort to quantify the potential economic effects of climate change on wildfire risk. Future studies will likely use refined models with better representation of geographic and distributional aspects of wildfire activity and damages.

Table 11: Studies of Wildfire Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
Howard, 2014	U.S., world	2050	A2

5.5 Small-Scale Storm-related Phenomena

This section reviews recent evidence on the impacts of climate change on small-scale storm-related phenomena. In Section 5.5.1, we discuss the physical mechanisms through which changes in the climate could affect small storms and their associated phenomena. Next, in Section 5.5.2, we explain the methodologies that have been used in studies that project damages due to these events. Finally, in Section 5.5.3, we summarize empirical projections of future storm-related losses.

5.5.1 Climate Change and Small-Scale Storms

Small-scale storm-related phenomena—such as hail, tornadoes, and thunderstorms—are capable of causing substantial amounts of damage in localized areas. However, predicting how climate change could influence these categories of extreme weather is difficult. Climate change will have both positive and negative effects on the physical processes that produce these events, and current climate models do not simulate these phenomena well (IPCC, 2012, p.13). Furthermore, due to improvements in reporting practices and monitoring technology, the historical record for these events is relatively poor (IPCC, 2012, p.141). As a result, the IPCC does not consider there to be enough evidence to make any consensus projections about the impact of climate change on these events.

There are also a limited number of region-specific studies that predict the effect of climate change on these small storm phenomena, primarily for hailstorms and thunderstorms. Hailstorms have been studied because they can cause significant damages to crops (Niall et al, 2005). Hail often occurs in thunderstorms, and hail formation is linked to strong vertical wind shear, strong upper-tropospheric winds, and low upper-air temperatures (McMaster, 1999). If climate change affects these variables (particularly upper-air temperature), hailstorm frequency and intensity could change.

One caveat for looking at the effect of climate change on thunderstorms and hailstorms is that while convective environments are relatively well-understood, the "triggering" of these storms is not (Marsh et al, 2008). For both thunderstorms and hailstorms, researchers have begun to look at the impacts on Convective Available Potential Energy (CAPE) under climate change (Marsh et al, 2008; Niall et al, 2005; Trapp et al, 2007). For example, Marsh (2008) predicts increased CAPE due to climate change in the Mediterranean, implying increased thunderstorms in that area, while Trapp (2007) predicts increased days with severe thunderstorm conditions (based on a CAPE calculation) in the Gulf of Mexico and Atlantic coast of the United States.

5.5.2 Methodologies for Modeling Small-Scale Storm Losses under Climate Change

This section discusses the scientific and economic methodologies used to forecast damages from small-scale storm-related phenomena under future climate change. At this time, we are only aware of papers that model losses as a result of hailstorms (Botzen et al, 2010; McMaster, 1999, Niall et al, 2005), and none that model losses for tornados or thunderstorms.

In order to predict future hailstorm losses, most studies look at projected upper-air temperatures and their relationship with historical reported losses from hail. Both McMaster (1999) and Niall (2005) apply the "TT Index," which calculates the probability of storms based on temperatures and pressures implied by downscaled data from GCMs. Niall (2005) also calculates CAPE under the changing climate. Niall notes a caveat for using the TT Index: while it is effective at predicting storms, it does not incorporate a moisture variable. Finally, using a slightly different methodology, Botzen et al (2010) extrapolates hailstorm damage from historical data based on a climate prediction of minimum and maximum temperature as well as precipitation. He also adds an additional variable for seasonality, as hailstorm damages are higher when they occur in spring and summer, due to increased crop losses.

5.5.3 Projections of Small-Scale Storm Losses under Climate Change

As described above, there is a lack of understanding of how thunderstorms, tornados, and to some extent, hailstorms, are impacted by climate change. As a result, there are limited studies predicting losses due to these types of storms.

Table 12 describes the three studies that we have identified that project future losses from hailstorms. Botzen (2010) predicts that damages to agriculture will increase 25-49% by 2050. McMaster (1999) predicts a 0.0 to 3.3% increase in crop losses, under a doubling of CO_2 levels. Finally, Niall (2005) predicts no significant change in convective energy in the study area, suggesting no change in crop losses. None of these studies report losses in currency.

There are many caveats associated with using these studies to look at future losses from hailstorms. The link between climate change, convective energy, and storms is not well-understood. Generating robust predictions about hailstorms and other storm-related phenomena will require additional research.

Table 12: Studies of Small-Scale Storm-Related Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
Hailstorms			
Botzen et al, 2010	Netherlands	2050	1°C, 2°C temperature rise
McMaster, 1999	Australia	n/a	CO_2 doubled
Niall et al, 2005	Australia	2040-2060	CO_2 doubled from pre-industrial levels

5.6 Landslides and Avalanches

This section reviews recent evidence on the impacts of climate change on economic losses from landslides and avalanches. In Section 5.6.1, we discuss the physical mechanisms through which changes in the climate could affect landslides and avalanches. Next, in Section 5.6.2, we explain the methodologies that have been used in studies that project damages due to these events. Finally, in Section 5.6.3, we summarize empirical projections of future landslides and avalanche losses.

5.6.1 Climate Change and Landslides/Avalanches

The movement of rocks, debris and snow in landslides and avalanches can cause damage to properties and infrastructure, and can result in loss of human life. Tourism and recreation in mountain regions increases exposure to the impacts of these events (IPCC, 2012, p. 258). Historically, these losses have been difficult to quantify, since smaller incidents often go unreported and affect less populous regions. In addition, the potential effects of climate change on landslides and avalanches are not fully understood, especially on a global level.

The main variables that predict land stability are cohesion, material density, slope angle, pore water pressure, and internal friction. There are several mechanisms through which climate change could affect these variables. For example, because the presence of water affects most of these variables, changes in rainfall or increased glacial melt could increase landslide frequency. In addition, higher temperatures may affect the permafrost and glacial ice that provide lateral support on slopes (IPCC, 2012, p. 186-189). However, climate change may cause increased evapotranspiration, resulting reduced water in soils, and thus requiring more rainfall to trigger landslides (Crozier, 2010 pg. 261).

The IPCC predicts that climate change is most likely to have impacts on avalanches and landslides in high mountainous regions. However, the net direction of the impact is still unclear (IPCC, 2012). Furthermore, because other human activities (such as development of unsafe locations) play a greater role in determining risks in lower altitude areas, there is little evidence on whether climate change could influence the shallow landslides that cause damage in the places where people typically live.

5.6.2 Methodologies for Modeling Landslide/Avalanche Losses under Climate Change

Modeling future landslide and avalanche risk under climate change involves two steps. The first step is to downscale a GCM, possibly using a regional climate model, to predict precipitation and evapotranspiration rates in the mountainous areas where these disasters occur. The second step is to predict future landslide risk by feeding the predicted change in local weather patterns into a model of the regional relationship between weather and landslide return periods (Crozier, 2010 pg. 262-263).

An important challenge to modeling losses from landslides and avalanches is that these disasters occur in less populous regions, and thus are difficult to observe (IPCC, 2012). Furthermore, human influence, especially increased deforestation and urbanization, increases risk of landslides due to greater slope instability and runoff (Crozier, 2010). Thus, predicting future losses requires accounting for both poor historical data and for the potential effects of migration and development in mountainous regions that are more at risk from landslides or avalanches.

5.6.3 Projections of Landslide/Avalanche Losses under Climate Change

We have identified only one study that estimates losses from landslides or avalanches as a result of climate change: Roson (2006). The study uses a multi-country CGE model based on historical damages. It predicts an increase of $7 million in annual damages from landslides in 2050 in Eastern Europe and the former Soviet Union, but finds statistically insignificant changes in losses in all other regions. Table 13 summarizes some key characteristics of this study.

Table 13: Studies of Landslide and Avalanche Losses under Climate Change

Study	Geography	Time Period	Climate Change Scenario
Roson et al, 2006	World, by region	2050	1.04-1.75°C increase, by region

5.7 Summary of Parameter Estimates

This section summarizes model parameters that describe the effect of climate change on damages from extreme events. In the notation of Section 2, this section focuses on the function $C_i(\Delta T_t)$, which is defined as:

$$C_i(\Delta T_t) = (1 + \tau_i)^{\Delta T_t}$$

where i denotes region and $1 + \tau_i$ is assumed to have a lognormal distribution:

$$\ln(1 + \tau_i) \sim N(\mu_i, \sigma_i)$$

Table 14 summarizes estimates of the parameters μ_i and σ_i that define the distribution of effects for each type of disaster and region. These estimates are drawn from the meta-analysis results presented earlier in this section. As noted previously, these estimates should be interpreted cautiously. For many regions and types of disasters, there is insufficient evidence in the research literature to develop estimates of appropriate parameter values. In these cases, the table shows a "na" value.

Table 14: Parameters Describing the Effect of Climate Change on Disaster Losses, by Disaster and Geography

	Region	Tropical Cyclones	Extra-tropical Cyclones	Inland Floods	Wildfires	Small Storms	Landslides and Avalanches
τ_{NA}	North America	0.154 (0.182)	na	0.274 (0.266)	na	na	na
τ_{SA}	South America	0.154 (0.182)	na	na	na	na	na
τ_{EU}	Europe	0.154 (0.182)	0.078 (0.063)	0.274 (0.266)	na	na	na
τ_{AF}	Africa	0.144 (0.167)	na	na	na	na	na
τ_{AS}	Asia	0.063 (0.168)	na	na	na	na	na
τ_{AU}	Australia	0.144 (0.167)	na	0.274 (0.266)	na	na	na

Notes: Each cell in the table presents the mean μ_i for a particular region and type of disaster. The corresponding standard deviation σ_i is shown in in parentheses. Refer to the text above for detailed descriptions of what these parameters represent.

6 Empirical Application

The previous sections of this document review evidence on three topics: the magnitude of baseline damages from extreme weather, how damages are likely to change with socioeconomic growth, and how damages are likely to change due to climate change. In this section, we present a simple empirical application that combines these three strands of literature and uses them to project future costs from extreme weather under climate change.

Section 6.1 describes our general methodology, and then presents the predicted change in losses, by type of event and region. Section 6.2 then discusses limitations and uncertainties, with a focus on interpreting the results in light of adaptation possibilities.

6.1 Methodology and Results

To estimate future damages from extreme weather under climate change, we simply substitute the parameters from Table 4, Table 7, and Table 14 into the damage function presented in Section 2. We then evaluate the model predictions for a scenario that involves a +2.5°C change in temperature. For simplicity, this initial application assumes that population and GDP remain constant at their current levels in all regions of the globe. Additionally, we run the model only for regions and types of extreme weather for which reasonable parameter estimates are available.

To capture uncertainty related to the model parameters, we develop estimates by running a Monte Carlo simulation in which we draw 500 different realizations from the distribution of potential parameter values. For each draw, we calculate current and future losses. We then calculate the average loss across these different draws, as well as a 95 percent confidence interval.

Table 15 presents the results of this empirical exercise, for tropical cyclones, extratropical cyclones, and inland floods. Baseline losses for tropical cyclones are largest in North America and Asia. Under a +2.5°C increase in temperature, mean losses in these two regions are predicted to increase by $12 billion (63%) and $2.2 billion (28%), respectively. However, the confidence intervals on these estimates are very wide. For example, in North America, a 95% confidence interval ranges from a $8 billion decrease to a $49 billion increase.

Table 15 also estimates the effects of climate change on extratropical cyclone damages in Europe. Baseline damages are about $2.0 billion per year, and climate change will increase those damages by 23%, equivalent to $460 million. This confidence interval is also wide, ranging from a 12% decrease to a 66% increase in damages.

Finally, Table 15 presents estimates of how inland flooding losses will be affected by climate change, for North America, Europe, and Australia. If global surface air temperatures increase by +2.5°C, inland flooding losses in these three regions are expected to increase by $3.7 billion, $6.4 billion, and $0.7 billion. Since this report does not review any research directed at assessing climate change impacts on inland flooding in Asia, Table 15 does not present predictions for Asia (which according to EM-DAT, has very high baseline losses).

Overall, Table 15 suggests two key messages. First, extreme weather losses could increase substantially as the climate change, with expected costs that range in the tens of billions of dollars. Second, the uncertainties surrounding these predictions are very large, with large decreases and increases in damages both possible.

Table 15: Predicted Change in Extreme Weather Losses under +2.5°C

Region	Tropical Cyclones	Extratropical Cyclones	Inland Floods
	Baseline Losses (millions, 2014$)		
North America	$18,671	$37	$2,548
South America	$0	$0	$0
Europe	$35	$2,010	$4,388
Africa	$61	$0	$275
Asia	$8,115	$0	$14,573
Australia	$368	$0	$508
	Change in Losses (millions, 2014$)		
North America	$11,740 [-$7,846, $48,548]	na	$3,744 [-$1,250, $16,177]
South America	$0 [$0, $0]	na	na
Europe	$22 [-$15, $91]	$463 [-$240, $1,321]	$6,447 [-$2,152, $27,858]
Africa	$34 [-$24, $138]	na	na
Asia	$2,255 [-$4,089, $13,606]	na	na
Australia	$207 [-$143, $832]	na	$746 [-$249, $3,225]
	Percent Change in Losses		
North America	63% [-42%, 260%]	na	147% [-49%, 635%]
South America	63% [-42%, 260%]	na	na
Europe	63% [-42%, 260%]	23% [-12%, 66%]	147% [-49%, 635%]
Africa	56% [-39%, 226%]	na	na
Asia	28% [-50%, 168%]	na	na
Australia	56% [-39%, 226%]	na	147% [-49%, 635%]

Notes: Each cell shows the baseline or mean predicted change in extreme weather losses, in either USD or in percentage terms. Numbers in brackets represent a 95% confidence interval, calculating using a Monte Carlo simulation. Changes in losses due to climate change are calculated relative to a present-day baseline that assumes no economic growth or population growth. The climate change scenario assumes a 2.5°C increase in global surface air temperature.

6.2 Accounting for Adaptation

Making predictions about the impacts of climate change on future extreme weather losses involves many uncertainties. Some of these are related to uncertainty about the appropriate values of the input parameters—e.g., uncertainty about the true baseline damages caused by tropical cyclones. These limitations are discussed in detail in the previous sections of this document. However, one key issue that is not discussed above is adaptation. If extreme weather events increase in magnitude or frequency in the future, then residents of affected areas are likely to invest in adaptation measures to prevent losses. These measures could take a variety of forms, including passing stricter building codes, investing in coastal armoring, building stronger levees, improving early warning and evacuation systems, using ecosystem-based features (such as mangroves or wetlands) to create coastal buffers, etc.

In principle, accounting for these adaptation possibilities requires estimating both investment costs and avoided damages from the adaptation effort. Doing so is a challenging exercise. For example, consider one likely avenue for adaptation to extreme weather: more stringent building codes. These codes are likely to increase building construction costs, due to the extra materials and labor required. They may also impose welfare costs on homeowners by limiting buildings' features or location (e.g., coastal residents may prefer to live in high-rise that located right on the beach, rather than at a safe buffer distance). Their benefits are also likely to be difficult to estimate. They require understanding how changes in building practices affect likelihood of damage during future extreme events, and how developers will respond to the new constraints. While there are engineering and economic approaches to estimating these types of costs and benefits, performing these calculations for each potential adaptation measure in each geographic area for each type of disaster would be a daunting exercise.

Nonetheless, in recent years, a small literature has begun to study adaptation to extreme weather. Three main themes emerge from this literature. First, there is strong evidence that regions that are more vulnerable to natural disasters make greater defensive investments. For example, Neumayer, Plumper, and Barthel (2014) find that nations that experience more frequent natural disasters are more likely to make defensive investments.

Second, there is also evidence that current defensive investments have prevented damage from extreme weather (Hsiang and Narita, 2012). For example, IFRC (2001) estimates that during the 1990s, worldwide investments of $40 billion in disaster preparedness, prevention, and adaptation reduced global economic losses by $280 billion. In a more specific context, Crompton and McAneney (2008) find that Australia's Wind Code—which sets building construction standards in regions frequently impacted by tropical cyclones—may have reduced storm losses. Similarly, Hsaing and Jina (2014) find that hurricanes cause less damage per knot of maximum wind speed in the countries in the highest quintile of average exposure. The authors attribute this declining marginal relationship to the higher defensive investments by these exposed countries.

Finally, a number of studies project that future adaptation efforts could at least partially mitigate the increased damages from extreme weather events caused by climate change (e.g., Neumann et al, 2014). For example, Ou-Yang et al (2013) project that in St. Lucia, investing in roof upgrades and strengthening windows and doors could reduce hurricane losses to wood-frame buildings by 24% under the worst climate change scenario (and 8% under the median scenario). The authors estimate that the benefit-cost ratio from these investments ranges from 2.1 to 3.5, based on a 20 year time horizon and a 5% discount rate.

Overall, failing to account for adaptation will result in overestimating net losses due to future extreme weather. Because this paper does not account for adaptation, we recognize that our estimates may be overestimates. However, incorporating adaptation into models of climate change impacts is currently a challenging exercise, and remains a subject for future research.

7 Conclusions

This report summarizes current research on how climate change is likely to influence future losses from extreme weather events. We consider three topics.

First, we examine research that estimates historical average losses from each type of extreme weather. We find that while there are relatively good data on reported costs of destroyed infrastructure, there is considerable disagreement in the literature about the longer-term macroeconomic effects of disasters.

Second, we summarize evidence on the relationship between socioeconomic growth and storm losses. Our review suggests that increases in GDP and population lead to higher losses from disasters, but that disaster mortality is lower in more developed countries.

Third, we review studies of how climate change will affect future losses from extreme weather. Many studies predict increases in losses under climate change, but the science remains uncertain and some projections suggest that certain types of extreme weather losses may decrease.

Overall, based on a reduced-form model that draws together parameter estimates from each of these three strands of literature, we estimate that moderate climate change will cause average extreme weather damages to increase by tens of billions of dollars per year. The uncertainties surrounding these predictions are substantial, with large decreases and increases in damages both possible. Furthermore, there is insufficient research currently available to make any predictions at all about some types of extreme weather events. Nonetheless, the synthesis parameters compiled in this paper represent a useful step towards developing improved IAMs that reflect the emerging scientific and economic literature on climate change and extreme weather.

Appendix A Tropical Cyclones

In the following subsections, we review background information on historical losses from tropical cyclones, discuss scientific evidence on how climate change could influence future tropical cyclone patterns, and then summarize existing projections of the potential impact of climate change on economic damages from these storms.

Appendix A.1 Historical Damages from EM-DAT

To characterize the magnitude and geographic distribution of damages from tropical cyclones, Table 16 summarizes information from the EM-DAT disaster database, broken down both by geographic region and by type of impact. The table shows that between 1985 and 2014, 298 storms struck Eastern Asia, 279 struck South-Eastern Asia, 204 struck the Caribbean, 134 struck Central America, 104 struck Southern Asia, 79 struck Eastern Africa, and 74 struck Northern America. These counts include only tropical cyclones that caused impacts that exceeded one of EM-DAT's disaster thresholds.

As the table demonstrates, the pattern of tropical cyclone losses depends on both geography and on levels of economic development. Although tropical cyclones occur in a number of regions, economic damages are concentrated in only a few locations. Average annual economic damages are $16 billion per year in Northern America, and $6 billion per year Eastern Asia. Average annual damages in Central America, the Caribbean, and South-eastern Asia are all between $1 and $1.6 billion, and damages in all other regions are less than $1 billion.

Economic losses from tropical cyclones are by far greatest in the wealthy countries of Northern America and Eastern Asia. However, these storms cause much greater loss of life, injury, and displacement in poor countries. For example, cyclones result in 6,000 deaths per year in both Southern Asia and South-eastern Asia. In contrast, annual storm-related mortality is 90 deaths per year in Northern America, and 421 deaths per year in Eastern Asia.

Although the figure does not present information about the range of annual losses in each region, there is considerable year-to-year variation in losses within particular geographies. For example, the EM-DAT database reports that Northern America damages in 2005 were $190 billion (largely due to Hurricanes Katrina, Wilma, and Rita), and damages in 2012 were $54 billion (largely due to Hurricane Sandy). In most other years, however, damages in this region have been substantially below the long-term average of $16 billion per year.

Table 16: Average Annual Tropical Cyclone Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts: People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	74	438,858	7	11,517	90	$15,668
Central America	139	427,779	727	20,588	765	$1,609
Caribbean	204	531,362	136	17,120	168	$1,394
South America						
South America	9	27,824	40	186	22	$18
Europe						
Western Europe	2	0	0	0	0	$0
Northern Europe	4	400	0	0	1	$14
Southern Europe	1	0	0	0	1	$15
Eastern Europe	10	735	4	10	2	$6
Africa						
Northern Africa	1	0	0	0	0	$0
Western Africa	2	57	0	123	0	$0
Eastern Africa	79	270,935	271	47,619	86	$61
Middle Africa	1	0	83	667	1	$0
Southern Africa	1	45	0	0	0	$0
Asia						
Russian Fed.	0	0	0	0	0	$0
Central Asia	1	0	0	50	0	$0
Western Asia	4	668	8	0	4	$183
Eastern Asia	298	8,923,088	1,847	79,372	421	$5,999
Southern Asia	104	3,611,957	8,990	213,191	6,045	$844
South-Eastern Asia	279	5,305,205	2,981	229,340	5,998	$1,089
Australia						
Australia and NZ	23	1,069	2	301	2	$261
Melanesia	49	34,422	6	3,700	18	$32
Micronesia	16	641	24	776	2	$31
Polynesia	33	11,015	10	1,189	2	$44

** This table is based on data for the 30-year period from 1985 to 2014.*
*** "People Affected" refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix A.2 Summary of Recent IPCC Findings

Table 17 summarizes the IPCC's key conclusions about the potential future impacts of climate change on tropical cyclones. The IPCC projects that worldwide, the frequency of tropical cyclones will remain constant or decline, but that heavy rainfall and mean maximum wind speed associated with these storms will increase. In some basins, it is "more likely than not" that the frequency of the most intense storms will increase (IPCC, 2013, p. 1220).

Table 17: Projected Impacts of Climate Change on Tropical Cyclones, from IPCC

Characteristic	Geography	Impact of Climate Change	Likelihood	Quality of Evidence	Citation
Frequency of storms	World	Decrease or Constant	≥66%	High	(IPCC, 2013, p. 1220)
Near-storm precipitation	World	Increase	≥66%	High	(IPCC, 2013, p. 1220)
Frequency of most intense storms	Some ocean basins*	Increase	≥50%	Medium	(IPCC, 2013, p. 1220)
Mean maximum wind speed	World	Increase	≥66%	High	(IPCC, 2013, p. 1220)

* *The IPCC does not provide information about the specific ocean basins that will be impacted.*

Appendix A.3 Studies of Economic Impacts under Climate Change

Table 18 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future tropical cyclone losses.

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
ABI (2009)	China	2°C global temperature rise and associated 13% rise in mean precipitation (4°C/26% and 6°C/39% sensitivity) and 3.7% increase in wind intensity (-0.5% and 7.9% sensitivity); "time independent"	Held constant	No correlation found between climate change models and the Royer cyclogenesis parameter: use mean and +/- 2 SD estimates of possible future tropical cyclone intensities using methodology and results adapted from Emanuel et al (2008); use Clausius-Clapeyron relation to relate precipitation increases to global mean temperature rise	Estimate **expected** annual insured loss, 100-year loss, and 200-year loss by applying climate scenarios to AIR Worldwide catastrophe model for China typhoons	Based on a 3.7% increase in intensity and a 2°C temperature rise (13% increase in mean precipitation), expected annual loss rises by 20.4%, 100-year loss rises by 6.7%, and 200-year loss rises by 13.8%
Bender et al (2010)	U.S.	A1B; 1980-2006	Held constant	Downscale GCM to RCM based on mean SST and seasonal mean climate to predict changes in hurricane frequency by intensity	Combines historical percentage of total damages attributable to each hurricane category and change in frequency of that category of hurricanes to estimate damage potential	28% increase in damage potential
Emanuel (2011)	100 Zones along the U.S. East and Gulf Coast	A1B; 2000-2100	Held constant	Downscales GCMs, based on using wind shear and thermodynamic state, to simulate landfalling hurricanes and uses a Poisson Distribution to create 100-year time series of events	Estimate total insured losses using a damage function, based on the cube of wind speed, and the estimated wind speed at the population-weighted center of the zone	Shift in the probability densities towards higher damage amounts for 3 of 4 GCMs
Esteban et al (2010)	Japan	Linear 1% annual CO2 increase (SST rise between 0.8°C and 2.4°C); 2085	Topography and population distribution are held constant but GDP annual growth rates of 1% and 2% were considered	Monte Carlo simulation with 4,000 runs: randomly generate tropical cyclone frequency based on a probability distribution and randomly selects a historical storm for each generated storm; then multiplies maximum wind speed throughout life of storm based on a randomly generated intensity multiplier from a probability distribution (also adjust radius of 30- and 50-knot areas based on max wind speed given regression results)	Estimate expected time loss for ports, assuming downtime for areas experiencing winds greater than 30 knots during a storm; also calculates needed increase in real port capital stock based on the relationship between RPCS and GDP and assumed GDP growth	An average increase of 18% to 43% in downtime for Japanese ports; 30.6 to 127.9 billion Yen potentially needed to expand ports to deal with increased downtime
Webersik et al (2010)	Japan	Linear 1% annual CO2 increase; 2085	Topography and population distribution are held constant and assume no change in GDP growth	Based on Esteban et al (2010)	Estimate expected time loss for 1,472 grids in Japan (same as Esteban et al (2010)) and then uses demographic factors and regional income values to estimate gross income for 119 grid cells to estimate GDP loss; areas with sustained wind speeds greater than 30 knots experience stop in economic activities	Lost man-hours leads to a 0.15% loss in annual GDP

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Esteban and Longarte-Galnares (2010)	Japan	Linear 1% annual CO2 increase; 2085	Constant and decreasing population (128 million in 2009 to 72 million) and subsequent working population per capita with 1% and 2% GDP growth rate	Same as Esteban et al (2010) but uses 5,000 simulations	Estimate expected time loss for ports, assuming downtime for areas experiencing winds greater than 30 knots during a storm; economic loss is measured as regional GDP times the additional number of hours lost in a year as a percentage of the total number of hours in that year	Decrease in Japanese economy of 6% to 13%
Raible et al (2012)	U.S.	A2, 2069-2100 (ECHAM5); and A1b, 2080-2099 (MRI/JMA)	Appears to be based on current conditions	Combines two AGCMs (ECHAM5 and MRI/JMA) with HURDAT best track data for cyclone tracking and detection to simulate a control and conditions under a changed climate and then scales simulated TC based on cumulative density functions of central pressures	Uses scaled simulated tropical cyclones, along with probabilistic events, and their characteristics(track, wind speed, etc.) to drive the hazard module of the Swiss Re loss model to determine loss frequency curves	20 year return period in control becomes 32 year return period in simulation and 80-year event becomes 110-year event(ECHAM5); 5 year return period in control becomes 3 year return period in simulation and 10-year event becomes 8-year event (MRI/JMA)
Hallegate (2007)	U.S. (11 regions)	10% increase in potential intensity; Not specified	Uses normalized damages to remove effect of population and economic growth	Develops a set of 3,000 synthetic hurricane tracks for current climate using a HURDAT and combines probability of a hurricane being a certain category (1-5) at landfall with probability of occurrence; then assumes 10% increase in potential intensity to generate tracks under modified climate	Relies on a damage function, based on the cube of wind speed, with a parameter for local vulnerability in each county	Rise in average normalized direct economic losses of 54% (rise in mean economic losses of $797 million per landfall and $534 million per track)
Mendelsohn et al (2011)	U.S.	A1B; 2100	Accounts for projected increase in local income and population	Uses climate models (CNRM,ECHAM, GFDL, MIROC) and a hurricane generator to create 5,000 storms per model and scenario and estimates the change in the distribution of hurricanes	Estimates two damage functions based on intensity(modeled on wind speed or barometric pressure) and income and population of 5 nearby coastal counties to evaluate property and infrastructure damage	Income and population growth expected to increase damages by $9 to $27 billion per year and climate change expected to increase damages by an additional $40 billion
Mendelsohn et al (2012)	World (by region)	A1B; 2100	Considers population increase and long-term growth rates of 2.7% for developing countries, 3.3% for emerging countries and 2% for developed countries	Uses climate models (CNRM,ECHAM, GFDL, MIROC) with a tropical cyclone model to generate 17,000 synthetic storms per model and estimate changes in frequency, intensity (based on pressure), and location	Estimate damage functions with wind speed, minimum pressure, income, and population density variables (for U.S. based on county data and for other countries based on country-level data) and project changes in expected damages and the probability distribution of damage	Increase in global cyclone damage of $53 billion per year due only to climate change (greatest damages in North America)

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
ABI (2005)	U.S., Japan	Assumed wind speed values for A1T, A1F1, A2, B1, B2, 550, and IS92a; 2020-2099	Socioeconomic variables held constant; analyze scenarios for reducing emissions by 2080	Use the assumption of 6% rise in wind speed associated with a 2.2 times increase in CO2 over 80 years (and 4% and 9% sensitivities); for IPCC scenarios, assume linear relationship between radiative forcing and wind speed	Apply assumed increases in wind speed to AIRS Worldwide model; use model outputs to estimate a loss curve and apply it to projected changes in wind speed under IPCC scenarios; adjust insured loss to total financial loss based on historical relationship between values	Increase in annual average financial losses in the U.S of $6.8 billion and $2.5 billion in Japan
Ackerman and Stanton (2008)	U.S.	A2; 2025-2100	Account for coastal development and higher population levels	Hold number of storms constant but assume storm intensity rises with surface temperature and sea-level will rise	Assume a doubling of economic damages and deaths for every meter of SLR and every doubling of atmospheric CO_2	Increase of $422 billion in damages and 756 deaths for 2100 (including all factors)
Bouwer and Botzen (2011)	U.S.	2.5°C rise in SST; Not specified	Uses normalized damages	Assume elasticity of maximum wind speed to temperature of .035	Estimate a damage function based on historical data that relates damage elasticity to the 8^{th} power of wind speed	96% rise in damages
Choi and Fisher (2003)	U.S.	13.5% and 21.5% rise in precipitation (mean and SD) based on meteorological models for a doubling of CO_2; not specified	No change	Use climate change scenarios that predict increases in mean value and standard deviation of annual precipitation	Estimate a damage function for hurricanes based on changes in hurricane category, precipitation, and socioeconomic variables	13.5% increase in precipitation leads to greater than 100% rise in losses; 21.5% increase leads to greater than 200% rise in losses
ECAWG (2009)	South Florida (3 counties)	Baseline; 3% increase in wind speed and .08m SLR; and 5% increase in wind speed and .24m SLR; 2030	Estimate GDP in 2030 for region based on based on each counties' historical GDP ($316 billion)	Scenarios based on expert input: changes in wind speed based on relationship with SST and SLR based on projections across two ice flow outcomes	Rely on Swiss Re historical data and probabilistic loss models to develop baseline and 2030 baseline potential damage and then model impact of changes in wind speed and storm surge on damages	Rise in damages from 8.4% of GDP assuming no CC to 9.4% to 10.1%
ECLAC (2011)	Bahamas	Hurricane occurrence scenario based on historical data combined with SLR; 2011-2051	Do not appear to account for different socioeconomic scenarios	Consider the historical pattern in hurricanes and create a scenario with 11 hurricanes (5 major) affecting Nassau and surrounding area before 2051 (between 2011 and 2050 indicate 8 storms occurring with alternating between Category 1 and Category 4/5 every 5 years) and assume increased hurricane intensity and SLR	Rely on estimates from other papers for the percent of damage based on hurricane storm surges; determine potential damage to hotels, roads, and airports and then rely on findings from another paper for associated damages	$2.4 billion in damages by 2050 due to hurricane activity and gradual SLR
Fankhauser (1995)	World	Doubling of CO_2; Not specified	No change from baseline	Assume 40-50% increase in hurricane intensity	Base the number of future deaths and damages on historical values	Additional $3,229 million in loss (based on damages and value of statistical life for deaths)
Moore et al (2010)	Barbados	Five hurricane probability scenarios; 2071-2100	Appears to not account for change	Create five scenarios with varying probabilities for Category 3, 4, and 5 storms	Estimate damages per hurricane category to determine the number of rooms affected and then calculate lost tourism revenue and lost value added	Tourism revenue loss of $355.7 to 1,969.3 million, depending upon scenario

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Nordhaus (2010)	U.S.	Equilibrium doubling of CO_2-equivalent levels; Not specified	Assume storm damage, conditional on wind speed, is proportional to GDP to remove the effects of economic agrowth	Assume a semi-elasticity of maximum wind speed to SST of .035, based on previous studies, and assume that a doubling of CO_2 will lead to a 2.5°C rise in SST and assume no increase in frequency, based on GCM modeling results (conduct sensitivities with other semi-elasticities)	Estimate a damage model based on GDP, hurricane frequency and wind speed; assumes damages are linear with frequency and related to the 9th power of wind speed (conduct sensitivities with other powers)	Increase in mean damages of 113%
Pielke (2007)	U.S.	550ppm in 2050; 2050	Two scenarios for change in global population and wealth in areas affected by hurricanes between 2006 and 2050 (2.8 times greater and 7 times greater)	Relied on an expert solicitation for changes in frequency and intensity; assumes no change in frequency based on midpoint of range and maximum increase in intensity (18% for 2050 and 36% for 2100)	Estimate damages assuming that damages are proportional to the 3rd, 6th, and 9th power of wind speed	480% rise in damages (assuming 180% rise in population/wealth, 18 rise in intensity, and 3rd power of wind speed)
Pielke et al (2000)	World	A1, A2, B1, B2; 2050	Estimates the effect of population growth and GNP growth by finding change in each between 2000 and 2050 and multiplying by the estimated baseline damages (for each SRES scenario)	NA	Assumes baseline damages for the world are twice U.S. damages and multiplies by the percentage increases in damage estimated by Cline (1992), Fankhauser (1995), and Tol (1995)	The 2050 annual damages from population and GNP growth only varies between \$32 billion and \$58 billion while the climate change only annual impacts are \$14.2 billion to \$15.3 billion
Ranger and Niehorster (2011)	Florida	A1B; 2020 and 2090	Exposure and vulnerability yare held constant over time	Rely on others' dynamically downscaled models (Bender et al (2010) and Emanuel et al 2008)) with adjustments for consistent baseline, emissions scenario, etc. (e.g. linear interpolation of reported values to determine impacts in desired years)and statistically downscaled models based on variables for SST and windshear; use 5-year averages to remove annual natural variability but doesn't account for decadal variability	Use probability-loss data from Risk Management Solutions to estimate wind-related residential property damage in Florida based on changes in frequency of all storms and frequency of Category 4 and 5 storms (to account for changes in intensity)	Some models show an increase in damages relative to the baseline while others show a decline (with a range roughly of -50% to 210% for 2020)
Schmidt et al (2009a)	U.S.	A1; 2015, 2050	Account for increases in wealth based on changes in capital stock (297% rise between 2005 and 2050 in capital stock in affected regions), which lead to a shift in the frequency distribution	Assume no change in frequency and base change in wind speed on a linear interpolation of the results of another study, which was based on A1 (3% rise in wind speed by 2050); use change in wind speed to shift a Poisson distribution describing storm frequency	Assume losses are related to the cube of wind speed and use a Monte Carlo simulation	Climate change alone will account for a 4% and 11 % rise in damages in 2015 and 2050, respectively

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Stanton and Ackerman (2007)	Florida	A2 (Business as Usual) and Rapid Stabilization; 2025-2100	Project future population and GSP and assume deaths are proportional to population while damages are proportional to GSP	Assume SLR of 7" and 45" by 2100 for Rapid Stabilization and Business as Usual cases, respectively	Assume damages double for every meter SLR and that damages double from a doubling of CO_2 concentration (based on change in intensity of storms)	Increase in hurricane damages of $6 billion by 2025 and $104 billion by 2100 for Business as Usual case over the Rapid Stabilization case
Narita et al (2009)	World (16 regions)	EMF 14 standardized scenario; 2100	Model includes exogenous scenarios of population growth and economic growth	Estimates changes in max wind speed using a parameter value of .04 for change in wind speed relative to a 1 degree change in regional SST, where regional SST is estimated based on its relationship with global avg. SST	Estimate a damage function based on changes in GDP and relative to the cube of max wind speed (the parameters for each variable are varied in sensitivities) – parallel analysis done for mortality (use version 3.4 of FUND)	Increase in total economic damages (damage and value of lost lives) of $25 billion
Neumann et al (2014)	U.S. (17 mulit-county areas)	3 emissions scenarios 2100	Use contour analysis to determine if property in each grid cell is at risk from all storms, or storms that overcome adaptation measures; estimate adaptation measures for at-risk cells in each time period based on the comparison of storm surge damage to property value and adaptation costs	Make adjustments to U.S. EPA's National Coastal Property Model using a location-specific cumulative distribution function for storm surge estimated using GCM outputs for SLR (for each emission scenario) and inputting wind field output from a tropical cyclone simulation based on Emanuel et al (2008) into NOAA's Sea, Lake, and Overland Surge from Hurricanes model to determine surge depths for simulated future storms; for the West coast, not affected by tropical cyclones, historic extreme events are used to estimate future high water events under SLR	Further adjust the NCPM with a cumulative distribution function for surge damage found by combining damage for historical periods with estimated future damages, found by estimating the annual expected value of damages (based on damages for eight specified return periods on the storm surge exceedance curve); then estimate damages for all property below the elevation specified for a future 500-year storm surge; extrapolate damages to unmodeled coastal counties by estimating SLR-only damages and using a multiplier from a modeled county (SLR-only costs to SLR and storm surge costs)	Cost of adaptation between $470 and $610 through 2100 for the reference emission scenario (also estimate results for two scenarios that lead to stabilized radiative forcing levels of 4.5 W/m2 and 3.7 W/m2, respectively)
Hsiang and Jina (2014)	World (by country)	A1B; 2090	Appear to estimate changes to baseline GDP (therefore excluding effects of socioeconomic growth)	Use results from Emanuel et al (2008) describing changes in cyclone power dissipation by basin	Estimate the present discounted value of tropical cyclone climate by estimating the impact of a tropical cyclone on income in the 20 years following a tropical cyclone and assuming in years 21+ a permanent, steady state loss equal to the loss in year 20	Loss of 5.9% of GDP for the United states (present discounted value with 5% discount rate)

Table 18: Projected Impacts of Climate Change on Tropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Peduzzi et al (2012)	World	Based on Knutson et al (2010); 2030	Project changes in exposed population and GDP for the year 2030	Interpolated estimated changes for 2030, using results of Knutson et al (2010), in frequency and max wind speed (percentage changes) and assumed that change in exposure relative to frequency was linear and that the distribution of storms by category shifted based on the percentage change in max wind speed; then found the average impact of intensity on land to create a ratio to determine change in exposure	Used a population model from Landscan 2008 and a GDP model from the World Bank to estimate exposure to storm events	Decreased storm frequency reduces exposed population in 2030 from 149.3 million to between 135.5 and 144.6 million
Toba (2009)	CARICOM	A1B; 2080	Based on 2007 economy	Rely on an estimate from Suzuki et al (2007) that hurricane landfalls per year will rise by 27%	Estimate direct damages and value lives lost as lost workforce labor effect on GDP; assume tourism expenditure decreases by an additional 4.6% (plus 17% baseline) due to hurricanes	Flood damage will rise by $363.1 million and windstorm damage will rise by $2,612 million; $446.9 decrease in tourism
Roson et al (2006)	World, by region	1 to 1.75 deg C warming by 2050; 2050		Estimate change in frequency of storms by estimating the relationship between frequency and 3 ENSO states and 2 NAO states; then estimate the probability of occurrence for each state based on changes in global temperature	Use a general equilibrium model for global economy and a regional growth model; run the models by translating changes in tropical cyclone damage to changes in saving	

Notes: In addition to the studies described in this table, several other research efforts have investigated the effects of climate change on tropical cyclone damages, including Seo (2014), Bjarnadottir et al (2014), Bjarnadottir et al (2011), Chavas et al (2013), Irish et al (2010), Esteban et al (2009), Emanuel et al (2012), and Esteban et al (2014).

Appendix B Extratropical Cyclones

The following subsections present data on historical losses from extratropical cyclones, discuss scientific evidence on how climate change could influence future extratropical cyclone patterns, and then summarize existing projections of the potential impact of climate change on economic damages from these storms.

Appendix B.1 Historical Damages from EM-DAT

Extratropical cyclones can cause damages through several different mechanisms, including strong winds and storm surges. In some cases, extratropical cyclones may also be associated with heavy rain or snow, which in turn may lead to further economic impacts (Donat et al, 2011; ECAWG, 2009; Mass & Dotson, 2010).

To characterize the magnitude and geographic distribution of losses from these storms, Table 19 displays average baseline damages from extratropical cyclones for the world regions contained in the EM-DAT database. The figure shows that extratropical cyclones have the greatest economic impact in Western Europe, where average losses are approximately $1.5 billion per year. Damages are about $0.4 billion per year in Northern Europe, $0.1 billion per year in Southern Europe, and less than $0.1 billion per year in Northern America and Eastern Europe. Substantial damages are not reported in other regions.

As with tropical cyclones, there is considerable variation in losses across years. For example, in Western Europe, the 20-year average losses are substantially higher than the 30-year year average losses, due damages in 1999 being more than twice as great as damages in any other year.

Note that this figure includes only damages from storms designated as “extratropical cyclones” in EM-DAT. To the extent that some storms classified in EM-DAT as “winter storms” may in fact be extratropical cyclones, the historical damages here may be understated.

Table 19: Average Annual Extratropical Cyclone Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts				
		People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	1	0	0	0	0	$37
Central America	0	0	0	0	0	$0
Caribbean	0	0	0	0	0	$0
South America						
South America	62	40,703	103	2,873	36	$0
Europe						
Western Europe	50	130,023	8	0	9	$1,456
Northern Europe	28	950	0	0	4	$437
Southern Europe	10	0	0	0	1	$99
Eastern Europe	13	38	2	0	1	$18
Africa						
Northern Africa	0	0	0	0	0	$0
Western Africa	0	0	0	0	0	$0
Eastern Africa	0	0	0	0	0	$0
Middle Africa	0	0	0	0	0	$0
Southern Africa	0	0	0	0	0	$0
Asia						
Russian Federation	0	0	0	0	0	$0
Central Asia	0	0	0	0	0	$0
Western Asia	0	0	0	0	0	$0
Eastern Asia	0	0	0	0	0	$0
Southern Asia	0	0	0	0	0	$0
South-Eastern Asia	0	0	0	0	0	$0
Australia						
Australia and NZ	0	0	0	0	0	$0
Melanesia	0	0	0	0	0	$0
Micronesia	0	0	0	0	0	$0
Polynesia	0	0	0	0	0	$0

**This table is based on data for the 30-year period from 1985 to 2014.*
***People Affected refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix B.2 Summary of Recent IPCC Findings

Table 20 summarizes the IPCC's projections about the impact of climate change on extratropical cyclones. As the table indicates, the IPCC projects that anthropogenic influences will result in a poleward shift in tracks from these storms, although the magnitude will vary by hemisphere (IPCC, 2013, p.1220). This conclusion is based on indirect evidence, as well as on recent empirical observations of an ongoing poleward shift in extratropical storm tracks (IPCC, 2012, p. 119). Although regional storm activity will likely be affected by climate change, the specific details of regional predictions should be interpreted with caution, due current models' inability to capture all aspects of the way that extratropical cyclones form and change (IPCC, 2012, p. 119, 164-165; IPCC, 2013, p.1220). Overall, based on the IPCC's review, it is not clear whether climate change will actually affect the global intensity of extratropical cyclones, or is likely only to shift storm activity poleward.

Table 20: Projected Impacts of Climate Change on Extratropical Cyclones, from IPCC

Characteristic	Geography	Impact of Climate Change	Likelihood	Quality of Evidence	Citation
Global number of extratropical cyclones	World	Decrease by only a few percentage points	≥66%	High	(IPCC, 2013, p.1220)
Storm track latitude	Northern Hemisphere	Poleward shift, but with complicated dynamics	≥50%	Medium	(IPCC, 2013, p.1220)
Storm track latitude	Southern Hemisphere	Small poleward shift	≥66%	Medium	(IPCC, 2013, p.1220)
Winter precipitation associated with extratropical cyclones	Arctic, Northern Europe, North America, and Southern Hemisphere	Increase	≥90%	High	(IPCC, 2013, p.1220)

Appendix B.3 Studies of Economic Impacts under Climate Change

Table 21 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future extratropical cyclone losses.

Table 21: Projected Impacts of Climate Change on Extratropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
ABI (2009)	UK	-1.45° storm track shift (4.40°C and --7.28°C sensitivity); changes reported are meant to be time independent	Held constant	No correlation found between global temperature/climate sensitivities and storm track: Scenarios based on estimated changes in storm track	Estimate **expected** annual insured loss, 100-year loss, and 200-year loss by applying climate scenarios to AIR Worldwide catastrophe model for United Kingdom wind storms	Based on a -1.45° shift in storm track, expected annual loss rises by 25.3%, 100-year loss rises by 13.9%, and 200-year loss rises by 11.9%
Narita et al (2010)	World (16 regions)	EMF 14 standardized scenario; 2100	Estimates of damage are based on GDP in a given future year	Set the damage parameter for each hemisphere based on the results from 15 GCM runs which showed an 8% and 42% rise in intense storms in the Northern and Southern Hemispheres, respectively, from a doubling of CO2	Estimate increase in damage based on the estimated level of damage in a given region and the current GDP and assume linear increase in damage relative to CO2 concentrations (sensitivity analyses of this assumption); similar methodology for mortality estimates	Increase in damages of $3.3 billion (includes value of lost life) due to climate change and economic growth
Leckebusch et al (2007)	United Kingdom and Germany	A2 and IS92a; 2070-2099 or 2060-2100 (dependent on GCM)	98^{th} percentile wind speed is based on baseline (no adaptation) and scenarios (adaptation)	Rely on outputs from an ensemble of 4 GCMs	Rely on a regression analysis and damage model that is based on the cube of normalized wind speed above the local 98^{th} percentile threshold times population density	Increase in loss potentials of 37% and 21% for the UK and Germany, respectively, without adaptation
Pinto et al (2007)	Europe (by country(ies))	A1b and A2; 2060-2100	98^{th} percentile wind speed is based on baseline (no adaptation) and scenarios (adaptation)	Use an ensemble of simulations of a coupled atmosphere-ocean GCM to estimate the daily maximum wind speed for each grid point	Calibrate a storm loss model, using data for Germany, based on the cube of normalized wind speed above the local 98^{th} percentile threshold times population density	Average increase in insured loss potential of 6.3% for A1B and 13.3% for A2, with adaptation
Pinto et al (2010)	North Rhine-Westphalia, Western Germany	A1B and A2; 2060-2100	Consider scenarios both with and without adaptation	Dynamically/Statistically downscales GCM data with a mesoscale model to estimate occurrence of storms and develop parameters to model wind gusts	Estimate an exponential loss function based on normalized wind gust values above a 98^{th} percentile threshold and a power slightly lower than 5	Rise in average annual loss of 8% and 19% for A1B and A2, respectively
Pinto et al (2012)	Core Europe	B1,A1B, and A2; 2060 to 2100	98^{th} percentile wind speed is based on baseline (no adaptation)	Rely on multi-scenario ensemble experiments using an atmosphere-ocean coupled GCM to estimate wind maxima	Calibrate a storm loss model, using data for Germany, based on the cube of normalized wind speed above the local 98^{th} percentile threshold times population density, with wind maxima estimated for a 24 hour period to calculate a moving loss index; also calculate a meteorological index that is not weighted by population density; estimate return periods using a generalized Pareto distribution based on identified event values over a specified threshold	For long return periods, loss frequency estimated to increase by a factor of 1.8 to 3.9 (depending on scenario)

Table 21: Projected Impacts of Climate Change on Extratropical Cyclone Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Held et al (2013)	Germany	A1B; 2070 and 2100	Assume constant relationship between storms and losses (no adaptation)	Use an atmospheric-ocean coupled GCM and (1) dynamically downscales synthetic storms using temperature estimates and an RCM and implements a model with a wind gust parameterization (varying storm nesting region); (2) statistically downscale using RCM and matching observed days with days in simulation (analogy method); and (3) group large-scale atmospheric patters into weather classes (WC), simulate WC with an RCM to estimate wind speed and maximum gust by grids, and then downscale combined WC to small-scale wind speed/gust climatologies, weighting by WC frequency (statistical-dynamical downscales)	(1) use a storm damage model based on the third power of normalized wind speed above the 98th percentile threshold; (2) use RCM output and regression analysis to develop future loss ratio (also third power of wind speed); and (3) develop, through regression analysis and Weibull distribution, probabilistic loss-transfer-function based on modelled wind speed	Increase in loss ratios for a 10-year return period of 6-35% for 2011-2040, 20-30% for 2041-2070, and 40-55% for 2071-2100
Donat et al (2011)	Europe	A1B; 2021-2050 and 2071-2100	98th percentile wind speed is based on baseline (no adaptation) and scenarios (adaptation)	Undertake 9 GCM runs and also downscale using 14 RCM simulations to create an ensemble; then, depending upon the RCM, use a gust parameterization or other method to estimate wind speeds	Use a storm damage model based on the third power of normalized wind speed above the 98th percentile threshold and population density, as a proxy for insured values; calibrate the model using historical data for Germany	With no adaptation, loss potentials in Germany estimated to rise by 37.7% (GCMs) or 15.1% (RCMs) by the end of the 21st century
Schwierz et al (2010)	Europe	A2; 2071-2100		Use output from a coupled atmosphere-ocean GCM to run two atmospheric GCMs, whose outputs are dynamically downscaled to two high resolution RCMs; use RCM output to determine changes in surface wind speed and frequency of heavy windstorm events	Use Swiss Re insurance model by selecting criteria for identifying significant storms, generating an event set using a Monte-Carlo approach, and calibrating losses based on historical data (based on selection of days with wind speeds 30% higher than 98th percentile threshold)	44% increase in annual expected loss
ABI (2005)	Europe	A2; time period not provided	Socioeconomic change was excluded	Increase of 20% in 20-year storm based on Leckebusch and Ulbrich (2004)	Apply assumed changes in storms to AIRS Worldwide model; adjust insured loss to total financial loss based on historical relationship between values	Increase in average annual average financial losses of $800 million

Notes: In addition to the studies described in this table, several other research efforts have investigated the effects of climate change on extratropical cyclone damages, including Hanson et al (2004), Dorland et al (1999), Roson et al (2006), Della-Marta et al (2010), Donat (2010), Heck et al (2006), Donat et al (2011b), Karremann et al (2014), Karremann (2015), and Held et al (2013).

Appendix C Inland Flooding

The following subsections present data on historical losses from inland floods, discuss scientific evidence on how climate change could influence future flood events, and then summarize existing projections of the potential impact of climate change on economic damages from inland floods.

Appendix C.1 Historical Damages from EM-DAT

Flooding can cause major damage to buildings and infrastructure, as well as agricultural damages (IPCC, 2012, pg. 259). To show how inland floods vary across regions, Table 22 shows number events and average annual impacts for all non-coastal flood events included in EM-DAT from 1985-2014[3]. Southern Asia has experienced the most inland flooding events, 441. In addition, there were 383 in South-Eastern Asia, 249 in Eastern Africa, and 246 in Eastern Asia, and many other regions also have substantial flooding events and associated losses.

As seen in the table, regions with greater average annual impacts are regions that experience frequent inland flooding events. However, regions that are more densely populated with more built-up infrastructure experience greater damages and number of people affected on average. Eastern Asia, which has the third highest number of flood events, has the highest damages, $9 billion, compared to $3 billion average damages in Southern Asia. Eastern Asia also has the highest number of people affected by a large margin, although Southern Asia experiences a higher average mortality rate of 1,969 compared to Eastern Asia's 971. In addition, Eastern Africa, whose total number of flooding events exceeds Eastern Asia by 4, only reports $49 million in damages and 292 mortalities, while North America, who has had 164 flooding events, faces $2 billion average annual damages and 24 mortalities.

[3] Coastal floods, as defined in the EM-DAT, are caused by changes in water level along the coast (Guha-Sapir et al, 2015) and therefore are quite different than the floods considered in this section of the report.

Table 22: Average Annual Inland Flood Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts: People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	141	404,491	12	1,360	24	$2,325
Central America	133	214,546	29	4,468	62	$188
Caribbean	73	68,328	13	4,170	135	$35
South America						
South America	271	1,223,236	317	44,736	1,270	$919
Europe						
Western Europe	66	12,122	0	0	8	$1,157
Northern Europe	34	12,178	0	1,000	2	$847
Southern Europe	123	114,856	11	1,188	27	$1,372
Eastern Europe	170	235,556	346	9,887	56	$1,012
Africa						
Northern Africa	90	224,866	677	49,298	143	$109
Western Africa	170	605,682	149	54,749	95	$35
Eastern Africa	249	628,919	50	38,507	292	$49
Middle Africa	89	98,821	65	11,825	42	$1
Southern Africa	51	69,240	12	2,157	47	$81
Asia						
Russian Federation	5	833	0	0	1	$47
Central Asia	34	27,653	37	908	10	$30
Western Asia	98	122,443	12	21,525	60	$213
Eastern Asia	246	59,844,154	25,095	1,228,497	971	$9,052
Southern Asia	441	18,383,605	729	434,789	1,969	$3,092
South-Eastern Asia	383	3,667,578	335	25,421	503	$2,139
Australia						
Australia and NZ	47	9,748	2	213	4	$496
Melanesia	23	13,358	0	1,667	4	$10
Micronesia	0	0	0	0	0	$0
Polynesia	2	0	0	0	0	$2

**This table is based on data for the 30-year period from 1985 to 2014.*
***People Affected refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix C.2 Summary of Recent IPCC Findings

Table 23 summarizes the IPCC's main conclusions about climate change and inland flooding. In selected regions where climate change is expected to cause increases in heavy precipitation, it is logical to expect that flooding may also increase. The IPCC's Fifth Assessment report notes that a number of case studies predict increased flooding in particular urban areas under climate change (IPCC, 2014, p.555). However, although there is good evidence that climate change will affect precipitation and snowmelt worldwide, the large number of factors that affect flooding makes it difficult to make global projections about future impacts of climate change on flooding (IPCC, 2012, p. 119). Overall, the literature on this topic is scarce, and so IPCC is unable to draw strong conclusions about whether anthropogenic influences will affect inland flooding via changes in heavy precipitation. Similarly, although the IPCC indicates that snowmelt-fed and glacier-fed rivers will probably experience earlier spring peak flows, there is little evidence that this will impact the frequency or intensity of flooding (IPCC, 2012, p. 175-178). Finally, due to a lack of existing literature, the IPCC draws no conclusions about pluvial floods.

Table 23: Projected Impacts of Climate Change on Inland Floods, from IPCC

Characteristic	Geography	Impact of Climate Change	Likelihood	Quality of Evidence	Citation
Frequency	World	Unspecified	Not quantified	Low	(IPCC, 2012, p. 119)
Flooding due to heavy rain	Some regions	Increase	Not quantified	Medium	(IPCC, 2012, p. 119)
Peak spring flows in snowmelt- and glacier-fed rivers	World	Occur earlier	≥90%	High	(IPCC, 2012, p. 119)
Floods from glacial lakes	High mountain areas	Not specified	Not quantified	High	(IPCC, 2012, p. 189).

Appendix C.3 Studies of Economic Impacts under Climate Change

Table 24 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future inland flooding losses.

Table 24: Projected Impacts of Climate Change on Inland Flooding Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
ABI (2009)	UK	2°C global temperature rise (4°C and 6°C sensitivity); changes reported are meant to be time independent	Held Constant	Met Office climate scenarios estimating correlation between global surface temperature change and precipitation: statistical downscaling of Hadley Centre GCM ensemble to RCM	Estimate **expected** annual insured loss, 100-year loss, and 200-year loss by applying climate scenarios to AIR Worldwide catastrophe model for Great Britain inland floods	Based on a 2°C rise in temperature, expected annual loss rises by 8%, 100-year loss rises by 18%, and 200-year loss rises by 14%
Aerts et al (2011)	Netherlands	0-150cm SLR (KMNI); 2015-2100	GE and RC	Model future maximum river water levels across dike-rings in Netherlands. Then adjust current flood probabilities by “Decimal Height”, a water level increase factor.	“Damage scanner” incorporates maximum flood depth across flood scenarios, projected land use, and stage damage functions. Simulates direct and indirect damages.	Varies widely across individual dike-rings in the Netherlands; overall increase in flood probability.
Bouwer et al (2010)	Netherlands	G, W+ (Kors et al); 2050	GE and RC	Increase 10-day precipitation sums result in increased discharge and higher flood probability. Assumes adaptations.	“Damage scanner” applies losses by land-use type and inundation depth; 5% accounts for indirect damages	Flood losses increase by 170%
Cheng et al (2012)	Canada	IPCC IS92a, SRES A2 and B2; 2046-2065 and 2081-2100	Held constant	Historical weather data downscaled to daily/hourly scale, which is input into simulation model based on weather-type and climate change to project frequency and intensity of flooding	Estimates losses using historical insurance data for rainfall-related water damage claims	Losses increase by 20-30%
Choi et al (2003)	US	Multiple changes in mean and standard deviation annual precipitation; no specified time	Held constant	Uses historical relationship between precipitation and flooding events	Regression analysis with OLS estimating method examines weather variability factors that affect flood losses by simulating mean and standard deviations of annual precipitation changes to model losses. Effects of inflation, population growth and growth per capita are eliminated.	1% increase in annual precipitation would lead to a 6.5% increase in flood losses
CLIMB (2004)	Boston	1% annual CO_2 increase and 2 GCM scenarios (CGCM1 and Hadley HadCM2); 2001-2100	Population and economic forecasts; 3 scenarios that account for society response to climate change	24-hour precipitation event likelihood (derived from climate scenarios) and imperviousness of basin (land use data) used to calculate projected probability of runoff-related river flooding	Direct damages – GIS land use data determines flood areas. Total damages determined by number of properties affected and costs based on historical values. Society response scenarios determine how many properties have been flood-proofed.	9118-3173 million USD increase over 100 year timeframe
Feyen et al (2009)	Europe, Madrid	SRES A2; 2071-2100	For Madrid only – A2 related socioeconomic changes – urban growth, population increase, etc	Modeled flooding probability with LISFLOOD model, climate change driven by HIRHAM RCM	Direct damages estimated by water depths projected on different land uses. Adaptations accounted for based on country GDP.	Most countries see increase in damages from 40-800%

Table 24: Projected Impacts of Climate Change on Inland Flooding Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Hall et al (2005)	England, Wales	UK scenarios based on SRES B1, B2, A2, A1F1 – precipitation decrease by 0-15% with higher intensity of winter precipitation	Foresight Futures scenarios – government autonomy vs. social value scale accounts for GDP, population, etc	Climate change scenarios increase water levels and lower "Standard of Protection" value for flood defenses	Risk model for each socioeconomic and climate scenario combination – incorporates land use, urbanization, flood-depth damage relationship. Damages are direct and include property and agricultural.	For high economic growth scenario, 20% increase in flood damages
Hallegatte et al (2010)	Mumbai	SRES A2 – 3.6 deg C increase, 6.5% increase in seasonal mean rainfall; 2080s	Held constant	Pluvial flooding model. Downscaled RCM used to create 200-year rain series. Use Storm Water Management Model to generate flood projections from simulated rain events for 50, 100, 200 year returns.	Historical insurance losses (direct), use Adaptive Regional Input-Output model to account for production losses and adaptations (indirect).	Total losses triple
Mokrech et al (2008)	East Anglia and NW England	UKCIP02, SLR 6-18cm default values; 2020s and 2050s	RS, GM, RE, GS based on A1, A2, B1, B2 for UKCIP02	Use a catchment descriptors method – increase in peak flow due to standard average annual rainfall (based on climate scenarios) and seasonal precipitation changes increases flood probability. Regional validation at baseline.	Uses RegIS with parameters for topography (flood duration), number of residential properties in flooding zone, number of people impacted based on socio-economic scenario, impact on agriculture (dependent on flood severity). Accounts for adaptations.	Increased flood risk, varies by region
Perrels et al (2010)	Finland	1-3 dec C increase, 2-12% precipitation increase, A1FI, A1T, A1B, A2, B1, B2; 2005-2050	Economic growth, building stock	Watershed model simulates daily discharge using Gumbel distribution based on flood magnitudes for return period of 100 and 250 years with inputs from climate change. Hydraulic modeling using HEC-RAS 4.0b.	GIS mapping of flood area to measure direct damages from repair/replacement costs based on water depth. Indirect tangible damages also considered – lost production days, lost revenue, cost of needed temporary housing.	Before adaptations: direct costs increase by 15%, impact on economic growth by 50%
Preston (2013)	US	n/a; 2025 and 2050			Project increase in per capita income/earnings and population growth to determine future exposure to extreme weather. Calculates losses due to changes in exposure	2025 – 1-1.4 billion USD increase; 2050 – 1.9-2.3 billion USD increase
Schreider et al (2000)	Australia	Doubled CO_2 and stochastic weather generator; 2030 and 2070		IHACRES model based on IUH technique predicts rainfall-runoff with climate scenario inputs; calibrated with historical data	SWG technique uses number of buildings affected and urban damage. Change in AGI estimated for probable maximum flood for 10-1000 year floods	Increase by factor of 2.5-9.8, varying by region
Te Linde et al (2011)	Europe, Rhine Basin	2 deg C increase with wetter winter/drier summer, SRES A1B (RCM is RACMO2.1); 2030	GE, RC	Land-Use Scanner downscales land-use projections from Eururalis model, with inundation map showing flood probabilities. Hydrological HBV model projects flood peak probabilities and discharge and used to adjust inundation map.	Damage Scanner assesses losses based on flooding area, water depth and land use. 5% is indirect damages	7.5-21% increase across region

Table 24: Projected Impacts of Climate Change on Inland Flooding Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
You et al (2001)	China	2.5 deg C increase from 1995-2100	Low, medium, high population growth scenarios; also account for government adaptation	Climate change will double flood damages	Dynamic programming model of flood control, parameterizes empirical damage functions with parameters from literature.	

Notes: In addition to the studies described in this table, several other research efforts have investigated the effects of climate change on inland flooding damages, including Nicholls et al (2005) and ABI (2005).

Appendix D Wildfires

The following subsections present data on historical losses from wildfires, discuss scientific evidence on how climate change could influence wildfires, and then summarize existing projections of the potential impact of climate change on economic damages from wildfires.

Appendix D.1 Historical Damages from EM-DAT

To illustrate the magnitude and regional distribution of economic losses from wildfires, Table 25 displays the average annual damages from wildfires, based on EM-DAT data. The table shows that wildfires cause the greatest average damage in Northern America, Southern Europe, and South-Eastern Asia. Large numbers of people also affected in Southern America, although damages there are lower.

Table 25: Average Annual Wildfire Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts: People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	82	29,422	21	852	5	$1,088
Central America	12	621	0	0	2	$9
Caribbean	3	0	0	0	0	$0
South America						
South America	30	10,353	19	207	4	$46
Europe						
Western Europe	7	208	5	0	1	$0
Northern Europe	1	0	0	0	0	$5
Southern Europe	49	39,117	15	155	8	$440
Eastern Europe	28	3,500	46	134	6	$83
Africa						
Northern Africa	3	0	0	0	3	$0
Western Africa	5	90	0	203	0	$0
Eastern Africa	3	0	1	100	2	$0
Middle Africa	4	3	0	122	0	$0
Southern Africa	10	83	18	195	4	$16
Asia						
Russian Federation	1	0	0	0	0	$0
Central Asia	1	267	0	0	0	$0
Western Asia	9	690	3	22	2	$12
Eastern Asia	16	2,170	10	55	10	$94
Southern Asia	6	0	0	1,800	3	$0
South-Eastern Asia	17	101,143	16	100	10	$447
Australia						
Australia and NZ	23	2,181	31	52	8	$96
Melanesia	1	267	0	0	0	$0
Micronesia	0	0	0	0	0	$0
Polynesia	0	0	0	0	0	$0

**This table is based on data for the 30-year period from 1985 to 2014.*
***People Affected refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix D.2 Summary of Recent IPCC Findings

The IPCC states that there is some evidence to support predictions of an increase in wildfire risk in Southern Europe and parts of Australia and New Zealand (IPCC, 2014). Other studies have also projected increases in wildfire risk in areas of Australia, South America, the western United States, and Canada (IPCC, 2012, p. 252-261).

These predictions are supported by more general evidence that droughts will rise in duration and frequency in certain regions of the world (southern Europe, central North America, Central America, Mexico, northeast Brazil, and southern Africa) under climate change (IPCC, 2012, p. 119). Furthermore, some studies have found evidence that climate change may already be affecting wildfire patterns in the Western United States and Canada (Gillett et al, 2004; IPCC, 2012; Westerling et al, 2006; Westerling and Bryant, 2008). These studies argue that observed increases in wildfires over the last several decades are related to rises in temperature and earlier snowmelt, each of which has been identified as a potential result of anthropogenic climate change.

Appendix D.3 Studies of Economic Impacts under Climate Change

Table 26 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future wildfire losses.

Table 26: Projected Impacts of Climate Change on Wildfire Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Howard, 2014	U.S., world	A2, 2050	None	Assumes U.S. wildfire incidence increases 50% by 2050	Assumes damages increase proportionally with incidence	By the year 2050, climate change will cause additional wildfire damages of $10 to $62.5 billion in the United States, and $50 to $300 billion worldwide.

Appendix E Small-Scale Storm-Related Phenomena (Hail, Tornadoes, Thunderstorms)

Small-scale storm-related phenomena—such as hail, tornadoes, and thunderstorms—are capable of causing substantial amounts of damage in localized areas. However, predicting how climate change could influence these categories of extreme weather is difficult. Climate change will have both positive and negative effects on the physical processes that produce these events, and current climate models do not simulate these phenomena (IPCC, 2012, p.13). Furthermore, due to improvements in reporting practices and monitoring technology, the historical record for these events is relatively poor (IPCC, 2012, p.141). As a result, the IPCC does not consider there to be enough evidence to make any consensus projections about the impact of climate change on these events.

In regions that become more dry and arid due to climate change, it is possible that the number of sand and dust storms will rise. There are a number of potential mechanisms through which this could occur, including changes in wind, precipitation, vegetation cover, and soil moisture. However, due to the uncertainty in projections about these mediating factors, the IPCC is unable to evaluate whether climate change will affect sand and dust storms (IPCC, 2012, p.190).

Although strong winds often occur as part of larger storm systems, they can also occur in other weather conditions. In general, there are few studies of how climate change could influence extreme winds. These studies focus on different geographies, and use different models—some of which have known limitations with respect to simulating extreme winds. Furthermore, the effect of changes in mean wind speeds on extreme wind speed is not well understood (IPCC, 2012, p.152). The only exception to this lack of understanding is for extreme winds occurring in tropical cyclones, which are discussed above in Section 3.2.

Extreme precipitation is typically defined in one of two ways. The first is set a threshold value in terms of percentiles and return values—for example, whether an event exceeds the average annual 95th percentile daily rainfall total recorded over a 20-year period. The second approach is to set an absolute threshold—for example, whether an event exceeds three inches of rainfall in a single day (IPCC, 2012, p. 141).

The following subsections present data on historical losses from extreme precipitation, discuss scientific evidence on how climate change could influence future extreme precipitation, and then summarize existing projections of the potential impact of climate change on economic damages from extreme precipitation.

Appendix E.1 Historical Damages from EM-DAT

Extreme precipitation can cause direct damages to buildings and stormwater/sewage infrastructure. It can also cause damages indirectly, though landslides, debris flows, flooding, and pollution (e.g., tailings dam failure) (IPCC, 2012, p. 249, 253).

To illustrate the magnitude and geographic distribution of damages from extreme precipitation, Table 27 shows average annual impacts from EM-DAT, by region, for convective storm events (excluding sand/dust storms) and snow/ice events over the past 30 years. Northern America experiences the highest number of damaging small scale storms, 283 between 1985 and 2014, and also exhibits the highest level of average annual damages at nearly $6 billion. As is the case with other events, the reporting of small scale storm-related phenomena occurrence may be understated due to the impact thresholds for reporting in EM-DAT.

Table 27: Average Annual Small Scale Storm-Related Phenomena Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts: People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	283	9,236	373	1,514	114	$5,699
Central America	4	17	2	0	1	$1
Caribbean	3	7,435	6	0	0	$50
South America						
South America	32	9,566	51	1,154	9	$9
Europe						
Western Europe	50	247	20	27	5	$396
Northern Europe	10	673	3	0	1	$98
Southern Europe	17	18,257	21	2	1	$48
Eastern Europe	27	1,300	10	1,082	7	$22
Africa						
Northern Africa	6	3,900	4	0	5	$10
Western Africa	10	2,810	1	1,122	7	$0
Eastern Africa	10	1,070	4	572	4	$0
Middle Africa	13	3,314	7	284	1	$0
Southern Africa	19	4,346	28	580	4	$32
Asia						
Russian Federation	1	0	0	0	1	$1
Central Asia	1	0	0	0	0	$0
Western Asia	13	73,907	124	333	3	$14
Eastern Asia	98	6,214,139	4,413	43,709	65	$539
Southern Asia	71	49,997	767	15,933	124	$124
South-Eastern Asia	18	2,212	8	427	4	$1
Australia						
Australia and NZ	28	15,931	5	35	1	$285
Melanesia	0	0	0	0	0	$0
Micronesia	0	0	0	0	0	$0
Polynesia	0	0	0	0	0	$0

**This table is based on data for the 30-year period from 1985 to 2014.*
***People Affected refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix E.2 Summary of Recent IPCC Findings

The primary mechanism through which global warming could affect extreme precipitation is via an increase in water vapor in the atmosphere (IPCC, 2012, p. 142-143).

Table 28 summarizes the IPCC's conclusions about the potential effects of climate change on extreme precipitation. At the global level, there is good evidence that the frequency of extreme precipitation events will increase (IPCC, 2012, p. 141-149). Individual storms are likely to become more intense (IPCC, 2013, p.1032). On a regional basis, the quality of future projections varies, but most areas are projected to experience increases in heavy precipitation. These conclusions are supported by the historical record, which suggests that the frequency of these heavy precipitation events increased between 1950 and 2000, with the most consistent evidence occurring in North America (IPCC, 2012, p. 119, 141-149, 196-201).

Table 28: Projected Impacts of Climate Change on Extreme Precipitation, from IPCC

Characteristic*	Geography	Impact of Climate Change	Likelihood	Quality of Evidence	Citation
Frequency or proportion of total rainfall from heavy precipitation events	Most of the world	Increase	≥66%	High	(IPCC, 2012, p. 119)
Total precipitation	Some regions	Decrease	Not quantified	Medium	(IPCC, 2012, p. 149)
HPD, HPC, and RV20	Canada and Alaska	Increase	≥66%	High	(IPCC, 2012, p. 196)
Heavy precipitation	North America (except Canada and Alaska) and Central America	Not specified (increase in some regions)	Not quantified	Low to medium	(IPCC, 2012, p. 196)
Heavy precipitation intensity and frequency in winter	Northern Europe	Increase	≥90%	High	(IPCC, 2012, p. 198)
RV20	Northern Europe	Increase	≥66%	High	(IPCC, 2012, p. 198)
Heavy precipitation intensity and frequency in winter	Central Europe	Increase	≥66%	High	(IPCC, 2012, p. 198)
Heavy precipitation intensity and frequency in summer	Central Europe	Increase	Not quantified	Medium	(IPCC, 2012, p. 198)
Heavy precipitation	Southern Europe and Mediterranean	Direction varies across regions	Not quantified	Low	(IPCC, 2012, p. 199)
Heavy precipitation	East Africa	Increase	≥66%	High	(IPCC, 2012, p. 199)
Heavy precipitation	Africa (except East Africa)	Not specified (no signal in most regions)	Not quantified	Low to medium	(IPCC, 2012, p. 199)
Heavy precipitation	South America	Not specified (increase in some regions)	Not quantified	Low to medium	(IPCC, 2012, p. 200)
Heavy precipitation frequency and intensity	North Asia	Increase	≥66%	High	(IPCC, 2012, p. 201)
Heavy precipitation	Asia (except North Asia)	Not specified (increase in some regions)	Not quantified	Low to medium	(IPCC, 2012, p. 201)

** HPD=number of heavy precipitation days; HPC=percentage contribution to total precipitation; RV20=20-year return value of annual maximum daily precipitation rates; DP10=percentage of days with 10 millimeters or more of precipitation*

Appendix E.3 Studies of Economic Impacts under Climate Change

Table 29 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future small-scale storm-related losses.

Table 29: Projected Impacts of Climate Change on Small-Scale Storm-Related Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Botzen et al, 2010	Netherlands	1-2 deg C temperature rise; 2050	Constant	Assumed a positive relationship between hailstorm damages and minimum seasonal (spring, summer) temperatures	Used normalized insurance data from hailstorm damages for agriculture and applied temperature variables from climate predictions provided by KMNI	Change in hailstorm damages for outside farming: Yearly scenario: 25-58% increase Summer scenario: 25-53% increase
McMaster, 1999	Australia	Basline CO_2 and doubled CO_2, 3GCMs (CCM1-Oz, BMRC, CSIRO-Mk2)	Constant	Calculated enhanced greenhouse gas effect for hailstorms based on the difference between seasonal variables obtained from the GCMs	The crop loss model applies upper air climatic variables to historical crop losses from hail	Net loss of 0-3.3% depending on climate model and location
Niall et al, 2005	Australia	CO_2 doubled from pre-industrial levels; 2040-2060	Constant	Assumed relationship between hail incidence and CAPE, which is calculated using climate data.	Uses crop loss insurance data and models the probability of hail storms based on climate variables	No significant change in crop loss damages due to hail storms for future climate scenarios

Appendix F Landslides and Avalanches

The following subsections present data on historical losses from landslides and avalanches, discuss scientific evidence on how climate change could influence landslides and avalanches, and then summarize existing projections of the potential impact of climate change on economic damages from these earth and snow movements.

Appendix F.1 Historical Damages from EM-DAT

To illustrate the magnitude and regional distribution of economic losses from these events, Table 30 displays the average annual damages for water-related landslides and avalanches, based on EM-DAT data. The losses shown in the figure exclude "dry" landslides and avalanches (Guha-Sapir et al, 2015). The figure shows that Eastern Asia has experienced the consistently highest average annual damages, of about $90 million per year. A few other regions also experience substantial losses, including Central and South America, Western and Southern Europe, and the Russian Federation.

Table 30 likely underestimates the total damages due to landslides and avalanches. For one, EM-DAT's disaster criteria requires either a minimum of 10 people reported killed, a minimum of 100 people reported effected, declaration of a state of emergency or call for international assistance; these criteria exclude smaller landslides that occur more frequently and have small but significant effects on communities. In addition, landslides are less frequent than other disasters, are underreported, and often occur in less populous areas. There is limited literature and data quantifying the losses due to landslides, but studies that attempt to quantify many disasters will sometimes include landslides. Often, landslides are grouped together with floods (for wet landslides and avalanches – these are called "hydrological" disasters) or earthquakes and volcanos (for dry landslides and rockfalls – these are called "geophysical" disasters) (Swiss Re, 2011; Worthington, 2004; Vos, 2009). In other studies, they are grouped with tropical cyclones or heavy precipitation events (Chiang, 2011). In fact, landslides were noted as being a weak point in one study, due to insurance companies often not covering damages from landslides and therefore making it difficult to estimate baseline damages (BTE, 2011). BTE (2011) estimates 1.2 million Australian dollars of annual direct and indirect losses from landslides in Australia (32 year average), but only large (at least $10 million cost, excluding death and injury) landslides were considered, so the average only reflects a single $40 million landslide (note that in Table 30, Australia as a region has $0 average damages). Hilker (2009) estimates 9.7, 14.9 and 0.4 million euros of direct losses in Switzerland from debris flows, landslides and rockfalls respectively (35 year average).

Table 30: Average Annual Avalanche and Landslide Impacts, By Region

Region	Total Number of Events, 1985-2014	Average Annual Impacts				
		People Affected	People Injured	People Homeless	Mortality	Damages (millions; 2014$)
North America						
Northern America	3	4	1	5	2	$1
Central America	21	296	4	1,707	18	$18
Caribbean	4	46	2	33	3	$0
South America						
South America	83	16,453	120	6,233	156	$62
Europe						
Western Europe	11	466	1	2	5	$56
Northern Europe	2	2	1	0	1	$0
Southern Europe	11	337	12	9	13	$41
Eastern Europe	9	27	0	11	14	$0
Africa						
Northern Africa	1	0	2	22	1	$0
Western Africa	5	0	0	393	3	$0
Eastern Africa	16	605	5	409	22	$0
Middle Africa	6	5	0	42	3	$0
Southern Africa	1	0	0	0	1	$0
Asia						
Russian Federation	3	0	0	83	4	$24
Central Asia	21	3,015	1	2,502	23	$12
Western Asia	13	364	8	80	17	$1
Eastern Asia	75	73,871	63	956	171	$93
Southern Asia	93	29,788	40	123,370	211	$3
South-Eastern Asia	86	26,514	36	4,404	135	$7
Australia						
Australia and NZ	2	3	0	0	1	$0
Melanesia	10	35	1	600	13	$0
Micronesia	0	0	0	0	0	$0
Polynesia	3	17	0	0	1	$0

**This table is based on data for the 30-year period from 1985 to 2014.*
***People Affected refers to the number of people requiring immediate assistance (e.g. food, water, shelter, medical assistance) during a period of emergency.*
**** Data for damages are converted to 2014 dollars using the U.S. GDP deflator (BEA, 2015).*
Source: Guha-Sapir et al, 2015

Appendix F.2 Summary of Recent IPCC Findings

Table 31 presents the IPCC's main conclusions about the impact of climate change on landslides and avalanches. As the table shows, the evidence is strongest that climate change will affect these disasters in high mountain regions, although the direction of the impact is unclear. Due to the impacts of human activities, there is little evidence on whether climate change could influence the shallow landslides that cause damage in the places where people typically live.

Table 31: Projected Impacts of Climate Change on Landslides and Avalanches, from IPCC

Characteristic	Geography	Impact of Climate Change	Likelihood	Quality of Evidence	Citation
Landslides affected by heavy precipitation	Some regions	Not specified	Not quantified	High	(IPCC, 2012, p. 189)
Shallow landslides	Temperate and tropical regions	Not specified	Not quantified	Low	(IPCC, 2012, p. 189)
Bedrock stability	High mountain regions	Not specified	Not quantified	Medium	(IPCC, 2012, p. 189)
Mass movements	High mountain areas	Not specified	Not quantified	High	(IPCC, 2012, p. 189).
Slope instabilities	High mountain areas	Not specified	Not quantified	High	(IPCC, 2012, p. 189)

Appendix F.3 Studies of Economic Impacts under Climate Change

Table 32 summarizes key information about the methodologies and results of selected studies that predict how climate change is likely to affect future landslide and avalanche losses.

Table 32: Projected Impacts of Climate Change on Landslide and Avalanche Losses

Study	Geography	Climate Scenarios and Time Periods	Socioeconomic Scenario	Climate Methodology	Economic Methodology	Predicted Change in Losses
Roson (2006)	World	1.04-1.75°C increase (by region), 2050		Increase in global temperature results in changes to ENSO and NAO oceanic oscillations (based on historical trends)	Multi-country CGE model estimates expected damages based on historical averages of victims and damages by disaster and region	Landslides statistically insignificant in all regions except Eastern Europe/former Soviet Union where $7 million additional damages are expected

Glossary

Avalanche: Movement of snow down a slope.

Extratropical cyclone: Extratropical cyclones are large-scale storm systems that form outside of the tropics, typically in mid-latitudes. They encompass a wide variety of phenomena, and are often referred to by weather forecasters as “lows” or “depressions”. For the purposes of this report, we focus on the most severe forms of extratropical cyclones—e.g., winter storms or wind storms in Europe, and nor’easters along the U.S. Atlantic Coast. Like tropical cyclones, these storm systems are associated with thunderstorms, strong winds, extreme precipitation, and waves and storm surges.

Extreme precipitation: Precipitation (rain or snow) that exceed some threshold, defined in relative (percentile or return values) or absolute terms (IPCC, 2012, p. 141)

Inland flood: Inland floods occur when water overflows from an existing body of water or when water accumulates over areas not normally submerged in water. Inland floods can be divided into several categories, including floods along rivers (“fluvial” floods), floods that occur when heavy precipitation completely saturates the topsoil (“pluvial” floods – most common in urban areas), and floods related to glacial lakes. The primary natural causes of flooding are extreme precipitation, melting snow or ice melt, and blockages to water flow, such as those caused by landslides (IPCC, 2012, p. 175).

HPD: Number of heavy precipitation days

HPC: Percentage contribution to total precipitation

DP10: Percentage of days with 10 millimeters or more of precipitation

Landslide: There are a number of disasters that occur in mountainous or hilly areas. These include landslides, in which soil, mud, or rocks slide down a slope; and avalanches, which involve snow (IPCC, 2012, p. 186). While these disasters can be caused by weather and climate conditions, they also result from geological conditions or from human activities (such as deforestation).

RV20: 20-year return value of annual maximum daily precipitation rates. In other words, the RV20 is the quantity of daily precipitation that large enough that it is expected to occur only once every twenty years.

Sea surface temperature (SST): The temperature of water close to the surface of the ocean or sea

Small-scale storm-related phenomena: Small-scale storm-related phenomena—such as hail, tornadoes, and thunderstorms—are capable of causing substantial amounts of damage in localized areas.

Tropical cyclone: Tropical cyclones are large rotating storm systems that form over tropical ocean areas. These storms—which are variously called hurricanes, typhoons, or cyclones—feature thunderstorms, strong winds, heavy rainfall, waves, and storm surges.

Vertical wind shear: The degree to which wind direction and speed change at different heights in the atmosphere

Wildfire: Wildfires are uncontrolled fires that burn in primarily undeveloped areas, such as farmland or wilderness. They are distinct from urban fires, which burn primarily buildings. Wildfires are complex events that depend on a variety of causal factors, including temperature and precipitation extremes.

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