CLIMATE CHANGE AND NATURAL DISASTER LOSS PREDICTION IN THE UNITED STATES

An Undergraduate Research Scholars Thesis

by

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RESEARCH COMPLIANCE CERTIFICATION

Research activities involving the use of human subjects, vertebrate animals, and/or biohazards must be reviewed and approved by the appropriate Texas A&M University regulatory research committee (i.e., IRB, IACUC, IBC) before the activity can commence. This requirement applies to activities conducted at Texas A&M and to activities conducted at non-Texas A&M facilities or institutions. In both cases, students are responsible for working with the relevant Texas A&M research compliance program to ensure and document that all Texas A&M compliance obligations are met before the study begins.

I, Jordan Vick, certify that all research compliance requirements related to this Undergraduate Research Scholars thesis have been addressed with my Research Faculty Advisor prior to the collection of any data used in this final thesis submission.

This project did not require approval from the Texas A&M University Research Compliance & Biosafety office.

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ABSTRACT

Climate Change and Natural Disaster Loss Prediction in the United States

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This project intends to answer the question of how rising disaster losses correlate to essential climate change variables. Despite the substantial upward trend in economic losses from disaster, there is still debate over whether anthropogenic climate change has been the main driver of losses. This is due to the need to control for complex socioeconomic variables such as population, social vulnerability, economic growth effects, and more. The project will investigate the effects of temperature, precipitation, and vulnerability on disaster losses to examine how these measures have predicted the human cost of disaster. I hypothesize that climate indicators will predict disaster damages, and that these effects will vary based on social vulnerability and physical exposure. I also predict regional climate data will predict damages more accurately than global data. By illuminating the variables that best predict losses and identifying quantitative trends, this project will quantify the relative contribution from anthropogenic climate change to disaster losses and provide helpful information about the predictive power of individual climate variables. Quantitative analysis of the secondary data will be conducted and the implications of climate change in the future will be discussed, as well as a review of the literature, especially in

the area of disaster attribution. The secondary data are available through NOAA, SHELDUS and NLDAS datasets. These data will be used to quantitatively study the relationship of specific climate variables to disaster losses. Correlation and regression analysis will be conducted on a county-level and global scale using Stata.

DEDICATION

Dedicated to the Hazard Reduction & Recovery Center at Texas A&M, including Dr. Michelle Meyer, Mason Alexander, Dr. Nathaniel Rosenheim, and Dr. Doug Wunneburger for helping me through the research process, as well as the professors and TAs who taught me all I needed to know.

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1. INTRODUCTION

Despite the continual rising of temperatures throughout the 1990s, studies prior to the mid-2000s have implied or outright stated that extreme weather events are impossible to trace back to anthropogenic climate change (Allen, 2003). The frequency and intensity of extreme weather such as El Niño, the 2017 wildfires, the 2020 Atlantic hurricane season, the 2021 freeze event in Texas, and extreme tornado outbreaks have put this into question. Recently, projections and models have been increasingly used to predict extreme weather and climate instability. As our understanding of the climate system has changed with new climate models' predictions (IPCC 2013), research has provided more than enough evidence that anthropogenic greenhouse gas emissions largely drive climate change.

There are still many uncertainties in the literature when it comes to specific estimates of the effect of climate change. The effects of climate change (precipitation, heat extremes, etc.) on the environment are complex, varying based on geography and natural variability (Nature Climate Change, 2019), which makes direct attribution difficult. The project will identify which markers of climate change have a substantial effect on natural disasters and the consequences of them. To facilitate better attribution, this paper will also test the relationships between climate variables to strengthen or disprove existing hypotheses. One such hypothesis, proposed by Liu et al. (2021), is that heavier precipitation predicts an increase in floods. Annual hurricanes have been predicted to increase by 50% for each 1 C increase in surface temperatures (Alvarez et al. 2021), temperature being one of the more predictive markers in the literature. To continue to understand the impacts of climate change, this paper will analyze essential climate variables alongside the rising cost of disaster.

An important mediator to consider between climate change and disaster damage is the built and social environment (Highfield et al. 2014). While hazard exposure captures structural characteristics of the built environment, social vulnerability captures the socioeconomic characteristics that impact hazard mitigation and recovery (Highfield et al. 2014). Extreme weather events of the past 30 years, as well as climate change in general, have had serious implications for vulnerable populations (Van et al. 2012; Meyer et al. 2021). A 1 °C rise in surface air temperature "would increase losses by between US$26 and US$88 billion", according to only nonlinear estimates (Estrada et al., 2015). While social vulnerability has been shown to correlate positively with losses (Fothergill & Peek, 2004; Bouwer, 2011), it has been accounted for with different methods, with differences between linear and nonlinear normalization procedures leaving a large room for uncertainty.

The research question will ask: how do specific indicators of climate change uniquely predict the losses incurred by natural disasters? The model will track different types of climate change markers and measure their individual ability to predict losses, while acknowledging complicated factors of vulnerability and exposure (Highfield et al. 2014). By studying climate variables that have already been established for prediction and analysis of disasters, quantitative trends in data can be identified. Investigating the relationships between these markers can strengthen our understanding of how climate change predicts disaster.

1.1 Definitions

The United Nations General Assembly standardized several terms in a 2020 report. Hazards are defined as "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation" (UNDRR, 2020). In short, it is a condition that poses a threat

(Flanagan et al. 2011). Disasters are defined as “a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts” (UNDRR, 2020). Exposure is “the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas” (UNDRR, 2020). Vulnerability refers to “the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards” (UNDRR, 2020). Social vulnerability, a subset of vulnerability, entails “socioeconomic and demographic factors that affect the resilience of communities” (Flanagan et al. 2011). Factors that tend to be included in this definition are race, ethnicity, poverty, gender, and age, among others (Highfield et al. 2014).

Losses in this paper and in the data refer only to direct losses (CEMHS, 2020; National Research Council, 1999), a monetary measure of the structural impact of hazards on physical infrastructure. Losses have also been referred to in the literature as economic damages, or cost of damages (Coronese et al. 2019). Meanwhile, disaster damage is typically referred to in physical units of destruction that occur immediately during or after a hazard event (UNDRR, 2020). Direct losses are easier to objectively measure than indirect losses. Indirect losses are effects such as business interruption due to a hazard, and are difficult to measure and sometimes intangible. Likewise, the complete loss data including direct and indirect losses would create much higher estimates than standard loss records (National Research Council, 1999). Lastly, land surface models (LSMs) are complex models that simulate several processes occurring at the Earth’s surface, such as evaporation, carbon emissions, or sunlight (Fisher & Koven 2020).

1.2 Literature Review

1.2.1 Temperature

Globally, there is a lot of natural variability associated with temperatures as a measure, especially when it comes to weather patterns influenced by heat oscillations. Notably, El Niño heat oscillations are irregular periodic fluctuations in sea surface temperature which can cause extreme weather in the eastern Pacific. Studies have found much higher likelihood of disasters with temperatures several standard deviations above the mean with concurrent warming of 1.25 C (Schär et al 2004). Natural variability is only part of the equation; "numerous factors have been shown to influence these local sea surface temperatures, including natural variability, human-induced emissions of heat-trapping gases, and particulate pollution" (Wuebbles et al. 2017). Generally, record-breaking extremes are found when natural variability overlaps with human-induced warming (Trenberth 2011).

According to NOAA's 2020 annual report, the combined land and ocean temperature has increased at an average rate of 0.13 degrees Fahrenheit (0.08 degrees Celsius) per decade since 1880; however, the average rate of increase since 1981 (0.18°C / 0.32°F) has been more than twice that rate. (Sánchez-Lugo et al. 2020) Global annual average temperatures have typically been derived from "integrated collection of historical temperature observations over the land and ocean." (Vose et al. 2012). Rise in global temperature has been 1.2°F (0.7°C). The acceleration of the warming can be attributed to increased greenhouse gases (Wuebbles et al. 2017).

In the United States, trends are similar. Temperature increases since 1896 have centered around 1.2-1.8 °F. In a Climate Science Special Report (Wuebbles et al. 2017), average minimum temperature increased at a slightly higher rate than average maximum temperature, which was confirmed in the NLDAS dataset used in the project. Additionally, warming and frequency (variance) of heat waves has intensified over the last 30 years (Wuebbles et al. 2017). However, regions of the Midwest have not followed suit, possibly because of anthropological agricultural conditions. This ‘warming hole’ where some regions have not experienced increases in warming in the southeast has been explained by the presence of other climate forcing, such as the prevalence of anthropogenic aerosols, which peaked from 1970-1990 (Leibensperger et al. 2012).

In terms of the utility of global and regional temperatures, global climate models generally have more use in understanding the broad consequences of warming, especially when implementing climate policy. Global temperature rise is often used as a yardstick for policy, with the Paris Agreement aiming to limit temperature rise under 1.5 C globally. Regionally, measured temperatures for a location may be average relative to the rest of the world, but might differ relative to what is typical for the geographical area (Peterson et al. 1997). Analyzing local temperatures can hint towards a possible deviation from the average for a given area. Additionally, using reference values computed on small scale establishes a baseline from which anomalies can be calculated. Anomalies are able to show weather trends and allow comparison between locations (Peterson et al. 1997). A recent report found that “recent increases in activity are linked, in part, to higher sea surface temperatures in the region that Atlantic hurricanes form in and move through. Additionally, studies have found evidence that ocean surface temperatures were linked to increases in strong cyclones (Graham & Diaz 2001).

1.2.2 Precipitation

Precipitation is the general term for rainfall, snowfall, and other forms of frozen or liquid water falling from clouds (Trenberth 2006). Precipitation amount, intensity, and frequency all vary with changes in climate (Trenberth 2008). Precipitation also affects trends in tropical storms and hurricanes. Flooding, which is associated with extremes in rainfall, is often driven by tropical storms or thunderstorms (Trenberth 2008). Hydrological models have been used in projections of future flooding, which often use rainfall and temperature, among other climate data. Land-surface models have also been used to evaluate climate change impacts on flooding (Madsen et al. 2014).

Peterson et al. (2008a) reported that in North America, heavy precipitation has been increasing over 1950-2004, as well as the average amount of precipitation falling on days with precipitation (Wuebbles et al. 2017). In the United States, precipitation is varied. While it has generally stayed at similar levels despite increases and decreases occurring in different regions, heavy precipitation events have increased in frequency and intensity since roughly 1979 (Wuebbles et al. 2017). Annual precipitation averaged across the contiguous United States has increased approximately 4% since 1901. Precipitation has decreased across the West, Southwest, and Southeast and increased in most of the Northern and Southern Plains, Midwest, and Northeast (Wuebbles et al. 2017). These events have also been found to increase by 6-7% per every degree Celsius increase (Wuebbles et al. 2017). Earlier studies have suggested a climate change pattern of wet areas getting wetter and dry areas getting drier (Greve et al. 2014). This simplified concept seems to be supported by the observations that generally, the southern parts of the US are experiencing a decrease in precipitation, and the northern parts are experiencing an increase. However, research in precipitation trends have used inconsistent terms and measurements, leaving it difficult to confirm this hypothesis or predict precipitation in the future (Roth et al. 2021).

Worldwide, there has been a ‘substantial’ increase in measures of Atlantic hurricane activity, including “intensity, frequency, and duration” (Wuebbles et al. 2017). Across global land areas, there has been a "slight" rise in precipitation, not statistically significant due to a lack of earlier data in the past century (Wuebbles et al. 2017). Despite only a small increase in precipitation, extreme precipitation events are becoming more frequent worldwide (IPCC 2013). Ntegeka & Willems (2008) found statistical significance in the historical increase in extreme rainfall over the past century.

Trends in precipitation and flooding have become a recent topic of interest with respect to a changing climate. These increasing surface temperatures "are very likely to lead to changes in precipitation and atmospheric moisture," and "more active hydrological cycle, and increases in the water holding capacity throughout the atmosphere" (IPCC 2001). Changes in heavy precipitation have occurred over the last three decades in eastern regions of the United States. Some research has measured a 14% increase in heavy precipitation (upper 5%) and a 20% increase in very heavy precipitation (upper 1%) according to Trenberth et al. (2008), with increases in extremes outweighing increases in mean precipitation. This helps support the wet-areas-wetter hypothesis, since the IPCC contends "it is likely that there has been a widespread increase in heavy and extreme precipitation events in regions where total precipitation has increased, e.g., the mid- and high latitudes of the Northern Hemisphere" (IPCC 2001).

1.2.3 Vulnerability

Vulnerability comes in many forms. Vulnerability is a factor which increases the susceptibility of an individual, a community, assets or systems to the impacts of hazards (UNDRR 2020). Social vulnerability is a more recently considered phenomenon that sheds light on damage patterns, as well as recovery and mitigation. Exposure and structural vulnerability are important determinants of damage sustained to structures. Population growth and wealth are main determinants of exposure. Exposure & vulnerability in different geographical areas has implications for the amounts of disaster losses.

However, when these factors are controlled for, social vulnerability continues to impact damage with lower-valued homes receiving more damage (Highfield et al. 2014). Community vulnerability can be described as susceptibility to harmful impacts of disasters (Zandt et al. 2012). Community vulnerability mapping has been used in hazard mitigation and disaster recovery planning (Van et al. 2012). Vulnerability to environmental hazards means potential for loss (Cutter et al. 2003), though there are different definitions of vulnerability in the literature. Based on socioeconomic status, extreme weather events have disproportionately impacted lower income communities (Fouillet et al., 2008; Elliott and Pais, 2006; Bullard and Wright, 2010). Climate change impacts relative to economic strength have been higher in low-income countries (Handmer et al., 2012). Increases in extreme events coincide with rises in vulnerability (Maarten K. van Aalst (2006), making it hard to disentangle which has caused the rising costs and by how much. This has led to a substantial increase in economic losses that has been mainly attributed to socioeconomic exposure (Preston, 2013). Since 1960, exposure has been increasing - sevenfold since the 1960s (O’Brien et al., 2006) - but spatially heterogenous (Preston, 2013) and influenced by path dependence.

However, there is still debate over whether anthropogenic climate change has been a driver of losses, due to the need to control for complex socioeconomic variables such as population, social vulnerability (Kashem et al., 2016; Fothergill & Peek, 2004; Berke et al., 2019), economic growth effects, and more (Bouwer, 2011). Only part of the literature identifies climate change as an explanation over commonly used socioeconomic variables (Estrada et al., 2015). There is no consensus within the social science community on a consistent measure of social vulnerability, though tools such as social vulnerability indexes have been created (Cutter et al. 2003). Vulnerability assessments have typically focused on housing construction and quality, with later research evaluating social characteristics as highly relevant.

1.2.4 Attribution

The area of disaster attribution in climate research is highly controversial; attributing observed changes in losses to climate change is difficult, given increasing coastal development and natural variability in storm patterns (Emanuel 2011); vulnerability is “increasing for reasons that have nothing to do with greenhouse-gas emissions, such as rapid population growth along coasts” (Pielke 2007). Researchers have suggested the increase in hurricane and tropical cyclone damages “may be due to anthropogenic climate change” (Ranson et al. 2014). Efforts to understand the effects of climate change on storm damages have therefore relied on predictive modelling. In Ranson et al. (2014), a quantitative analysis of cyclone losses, they found that across all models on average, a hypothetical 2.5 C increase in global air-surface temperature would cause hurricane damages to rise 63%. Models can have a wide range of predictions. Some studies have concluded that the Russian heat wave of 2010 was mostly “natural in origin”, (Dole et al., 2011), directly contradicting other authors such as Rahmstorf & Coumou (2011), whose work concluded that climate change was the main cause of the heat wave; up to 80%. A discrepancy in the literature has been the lack of information from certain time periods, undercounting of storms (Estrada et al., 2015) and other inconsistencies with models that have been used.

Attribution has come a long way. *Human contribution to the European heatwave of 2003* (Stott et al. 2005) was a groundbreaking paper which was the first of a series of attempts at more specific attribution of natural disasters. The conclusion of the paper was that human influence had “more than doubled” the risk of European summer temperatures as hot as the 2003 heat wave. In the years after, interest in the area grew at a rapid pace. A National Academy of Sciences report (2017) wrote that “an indication of the developing interest in event attribution is highlighted by the fact that in 4 years (2012-2015), the number of papers increased from 6 to 32.” In spite of the different opinions in various event attribution studies, the authors of Stott et. al (2005) stated that it is an “ill-posed question” whether or not climate change stands as a sole cause of the 2003 European heat wave, or other such events. Instead, their stance is that “…it is possible to estimate by how much human activities may have increased the risk of the occurrence of such a heatwave.” (Stott et. al 2005).

2. METHODS

2.1 Hazard Data

The hazard data is drawn from the Spatial Hazard Event and Loss Database for the United States version 19.0 (CEMHS, 2020). It is maintained by the Hazards and Vulnerability Research Institute and is mainly based on NCEI Storm Data as the original data source. Version 19.0 contains 925,847 loss records from 1960 to 2019 for 18 hazard types. The loss data is disaggregated at a county level, a detail level that allows for comparison with the county level temperature and precipitation data. The dataset works for the purposes of this project because, according to the NOAA, "no database offered the ability to download inflation-adjusted losses" (Gall et al. 2009), which allows for consistency over the years. Despite its helpful features, SHELDUS underrepresents drought events and overrepresents flooding (NWS 2007) due to difficulty recording droughts and required NCEI "guesstimates" of flooding (CEMHS, 2020). However, flooding and wildfires are two hazard types which are highly sensitive to climate conditions and will still be the main focus of the analysis.

Losses are equally distributed among counties if there is a multi-county hazard event, according to the documentation. "For instance, a thunderstorm event affecting Richland and Lexington County in South Carolina and causing property damages of $50,000 will be entered into the database as an event affecting Richland County with $25,000 and Lexington County with $25,000 worth of damage" (CEMHS, 2020). The losses are conservatively estimated. "Whenever losses are reported as a range… SHELDUS selects the lower bound of the range" (CEMHS, 2020). Between 1960 and 1995, loss estimates were given as a range rather than specific amounts, so losses were systematically lower. In 1995, specific amounts were given instead and spatial resolution also increased, leading to higher monetary accuracy (CEMHS, 2020).

2.2 Temperature and Precipitation Data

2.2.1 County

The North America Land Data Assimilation System (NLDAS) data available on the CDC WONDER website contains county-level daily average air temperatures ranging from 1979 to 2011 (NLDAS 2012). Max daily air temperature and min daily air temperature from the NLDAS dataset was used for regional temps and averaged to create a mean of temperature for use in regression analysis. NLDAS contains both real-time and retrospective hourly forcing data (Cosgrove et al. 2003). It is a land surface model with both data sets being produced using the same spatial and temporal methods and extensively quality controlled as a collaboration between several organizations, notably the National Oceanic and Atmospheric Administration (NOAA).

Local precipitation was from the NLDAS. The data available on CDC WONDER are county-level average daily precipitation observations in millimeters spanning the years 1979-2011 (NLDAS 2012). Reported measures are the number of observations and the range for the daily precipitation values. Data contains the 48 contiguous states and District of Columbia, stored by region, division, state, and county, and temporally (year, month, day).

2.2.2 Global

The global time series used for global surface temperature anomalies, the NOAAGlobalTemp data set, was derived from blended land and ocean data from the NOAA. It is a blend of the Global Historical Climatology Network monthly (GHCNm v4.0.1) and the Extended Reconstructed Sea Surface Temperature (ERSST v4) dataset for blended land & ocean data. It contains anomaly observations for each year from 1880-2021. Global precipitation was from the same NOAA source. Using temperature and precipitation anomalies can describe climate variation on a more granular scale than absolute measurements.

2.3 Techniques

Techniques include trimming dataset to 1990-2010, cleaning data, and merging datasets to make comparisons. Resources include North America Land Data Assimilation System (NLDAS) Daily Air Temperatures and Heat Index (1979-2011) available from the CDC, the NOAAGlobalTemp dataset, the Spatial Hazard Events and Losses Database (SHELDUS), social vulnerability data from the US Census and CDC, and Stata statistical data program.

The NLDAS data was downloaded from the CDC WONDER website for the years 1990-2010. SHELDUS data was then merged with minimum and maximum daily air temperature data from NLDAS. The two temperature variables were averaged to create a mean temperature variable seen in Tables 1.1-1.2. County-level precipitation data from NLDAS was also merged. Next, crop damage and property damage adjusted for 2018 were summed per county to create a total damage variable, also seen in Tables 1.1-1.2. Global temperature and precipitation from NOAAGlobalTemp dataset was merged. Two datasets, one containing only flooding hazards and one containing only wildfire hazards, were created out of the prior merged datasets. In the flooding dataset, 48 of 3,169 counties in the US did not experience flooding hazards. Therefore, missing observations of hazards were given a damage value of 0. In the wildfires dataset, 2,484 counties did not experience wildfires, and were given a damage value of 0. Descriptive statistics of seven weather variables and losses from flooding and wildfires datasets are shown in Table 1.1. A correlation analysis of five variables from both datasets was performed and shown in Table 1.5 and 1.6.

3. RESULTS

Table 1.1: Descriptive statistics of weather and losses

Summary statistics

	N	Mean	Std. Dev.	Median	min	max
Losses	3169	7804770.5	36314356	1639144.5	0	8.566e+08
Mean Temp	3111	13.22	4.592	13.09	-.704	24.941
Mean Precip	3111	2.707	.917	2.888	.25	7.655
Min Temp	3111	8.332	4.35	8.213	-5.378	21.883
Max Temp	3111	18.107	4.92	17.899	3.812	30.704
Global Temp	3169	.515	.014	.514	.465	.72
Global Precip	3169	1.194	.053	1.191	-.92	2.197

Displayed in Table 1.1 are summary statistics describing the number of observations, mean, standard deviation, median, minimum, and maximum of seven variables. The unit of observation is each US county over the 20 year period, of which 3,111 are not missing weather data. The table includes 15 possible hazard types categorized by SHELDUS. “Losses” refers to USD property and crop damage, summed together and adjusted for inflation to 2018. “Mean Temp” refers to minimum and maximum temperatures averaged together on the county level, which hovered around 13.2 C°. The min and max ranged between 8.3 and 18.1 degrees C°, with a standard deviation of four degrees. “Mean Precip” indicates daily average millimeters of precipitation. “Global Temp” and “Global Precip” are two measures that represent the change in global average – worldwide, temperatures rose 0.515 degrees Celsius, and precipitation increased by 1.194 millimeters over this period.

Table 1.2: Regression of Annual Losses

Regression results

Annual Losses	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Mean Temp	46550.596	178392.52	0.26	.794	-303092.32	396193.51	
Mean Precip	156192.9	882568.39	0.18	.86	-1573609.4	1885995.2	
Global Temp	12347017	2571853.4	4.80	0	7306276.9	17387757	***
Global Precip	279254.16	351679.54	0.79	.427	-410025.06	968533.39	
Constant	1943522	1209970.7	1.61	.108	-427976.96	4315020.9	

Mean dependent var	7819995.971	SD dependent var	141241796.494
Overall r-squared	0.001	Number of obs	66381
Chi-square	32.946	Prob > chi2	0.000
R-squared within	0.000	R-squared between	0.009

**** p<.01, ** p<.05, * p<.1*

Description of results – In Table 1.2, annual losses is the dependent variable. This table contains all hazard types. There are four independent variables, “Mean Temp” and “Mean Precip” again referring to county-level measures, while global temp and precip refer to a worldwide statistic. The variables are the same as in the previous table. In the results, global precipitation has a very statistically significant effect on annual losses, which is a total of all losses per year. This is interesting because global measures in Tables 1.5 and 1.6 did not reach significance. That may point to global measures being more useful in long-term observations of losses, as opposed to predictions of losses in specific hazard types, such as flooding and wildfires.

Table 1.3: Highest and lowest USD hazard losses

Across all years	All Types of Hazards		Flood		Wildfire	
All Counties		$519,000,000,000		$98,800,000,000		$17,000,000,000
	County Name, State	$	County Name, State	$	County Name, State	$
#1	Collier, FL	1.16e+10	Linn, IA	8.75e+09	Alameda, CA	3.13e+09
#2	Linn, IA	8.75e+09	Grand Forks, ND	4.69e+09	Los Alamos, NM	2.19e+09
#3	Lafourche, LA	7.75e+09	Davidson, TN	1.76e+09	San Diego, CA	1.53e+09
#4	Grand Forks, ND	4.71e+09	Jefferson, AL	1.37e+09	Orange, CA	9.10e+08
#5	Maricopa, AZ	3.24e+09	Polk, IA	1.23e+09	San Diego, CA	7.06e+08
Fifth to Last	Lebanon, PA	3.69	Payette, ID	9.61	Power, ID	428.58
Fourth to Last	Garfield, UT	3.08	Jefferson, AL	8.95	Douglas, WA	302.77
Third to Last	Trego, KS	2.92	Campbell, WY	8.69	Hawaii, HI	265.86
Second to Last	Morris, NJ	2.37	Ouachita, LA	8.24	Douglas, WA	230.31
Last	Nottoway, VA	0.16	Windham, VT	6.05	Jones, GA	175.57

Table 1.3 lists the largest and smallest disasters within each hazard type. This gives an idea of the scale of losses as well as some totals across the 20 years – the figure in the #1 category that caused $11,600,000,000 in losses was Hurricane Andrew in 1992, one of the most costly storms on record. The Iowa Flood of 2008 and Oakland Hills firestorm of 1991 are two of the other highest-loss disasters in their respective categories. Four out of five of the highest cost disasters took place in California, whereas the flooding events with the greatest losses occurred mostly in southeast regions of the United States; notably, not along coasts.

Table 1.4: Highest USD losses annually

Top County Each Year	All Types of Hazards				Flood				Wildfire			
	# of counties with damage	Avg. $ across Counties	County Name, State	County $	# of counties with damage	Avg. $ across Counties	County Name, State	County $	# of counties with damage	Avg. $ across Counties	County Name, State	County $
1990	2,762	7020516	La Salle, TX	9.61e+08	1,577	1445342	Brown, TX	1.92e+08	1	30.69376	Cascade, MT	97022
1991	2,753	3961975	Alameda, CA	3.13e+09	1,210	459563.2	Cameron, TX	9.22e+07	44	991851.4	Alameda, CA	3.13e+09
1992	2,772	2.15e+07	Collier, FL	1.16e+10	1,300	638522.1	Ocean, NJ	1.03e+08	1	31141.49	Boise, ID	9.84e+07
1993	2,955	1.30e+07	Polk, IA	1.28e+09	1,515	7205132	Polk, IA	1.23e+09	16	876578.8	Orange, CA	9.10e+08
1994	2,867	1308484	Chickasaw, MS	1.86e+08	1,275	185528.4	Price, WI	5.25e+07	159	7523.665	Larimer, CO	3388759
1995	2,657	8512143	Escambia, FL	1.29e+09	1,070	920919.1	Monterey, CA	5.45e+08	26	22047.58	Marin, CA	6.59e+07
1996	2,560	6526156	Pender, NC	3.85e+08	967	1323156	Jefferson, PA	1.60e+08	12	39074.01	San Diego, CA	5.99e+07
1997	2,497	6816421	Grand Forks, ND	4.71e+09	958	3449233	Grand Forks, ND	4.69e+09	13	21405.99	Yuba, CA	2.35e+07
1998	2,658	8461300	San Benito, CA	1.11e+09	1,134	1378011	Coffee, AL	2.03e+08	96	328567.4	Brevard, FL	3.12e+08
1999	2,569	7011751	Miami-Dade, FL	7.54e+08	810	852516	Somerset, NJ	5.40e+08	33	68009.21	Monterey, CA	1.01e+08
2000	2,449	5270516	Los Alamos, NM	2.19e+09	708	941665.8	Miami-Dade, FL	7.12e+08	71	975372	Los Alamos, NM	2.19e+09
2001	2,295	7773296	King, WA	1.41e+09	811	457373.4	Columbia, AR	1.70e+08	19	20350.85	San Diego, CA	1.74e+07
2002	2,361	3084237	Roseau, MN	2.79e+08	824	328193.7	Roseau, MN	2.79e+08	34	89596.89	Tulare, CA	8.37e+07
2003	2,384	6331069	San Diego, CA	1.55e+09	1,007	1127119	Jefferson, AL	1.37e+09	25	1001325	San Diego, CA	1.53e+09
2004	2,398	1.46e+07	Okaloosa, FL	1.78e+09	1,032	863081	Luzerne, PA	1.40e+08	23	7886.171	Riverside, CA	8582037
2005	2,344	5.56e+07	Lafourche, LA	7.75e+09	907	650602.7	Washington, UT	3.86e+08	48	15799.31	Callahan, TX	1.41e+07
2006	2,512	5214983	Columbia, WI	6.26e+08	730	1345529	Lake, OH	4.26e+08	84	165481.3	Siskiyou, CA	1.73e+08
2007	2,605	3601004	San Diego, CA	8.77e+08	876	587318.7	Burnet, TX	1.66e+08	69	503324.1	San Diego, CA	7.06e+08
2008	2,691	1.00e+07	Linn, IA	8.75e+09	1,089	4749184	Linn, IA	8.75e+09	79	74637.81	San Bernardino, CA	5.83e+07
2009	2,541	3105194	East Carroll, LA	8.20e+08	1,082	492143.3	Wayne, IA	2.93e+08	79	41128.51	Santa Barbara, CA	3.98e+07
2010	2,638	5459573	Maricopa, AZ	3.24e+09	1,193	1863447	Davidson, TN	1.76e+09	82	89917.88	Larimer, CO	1.26e+08

Table 1.4 is a series of statistics across the years 1990-2010, describing the number of counties that sustained damage, the average USD losses, and largest disaster for that year as well as its location. It is divided into all hazards, flooding, and wildfire hazard types, similarly to Table 1.3.

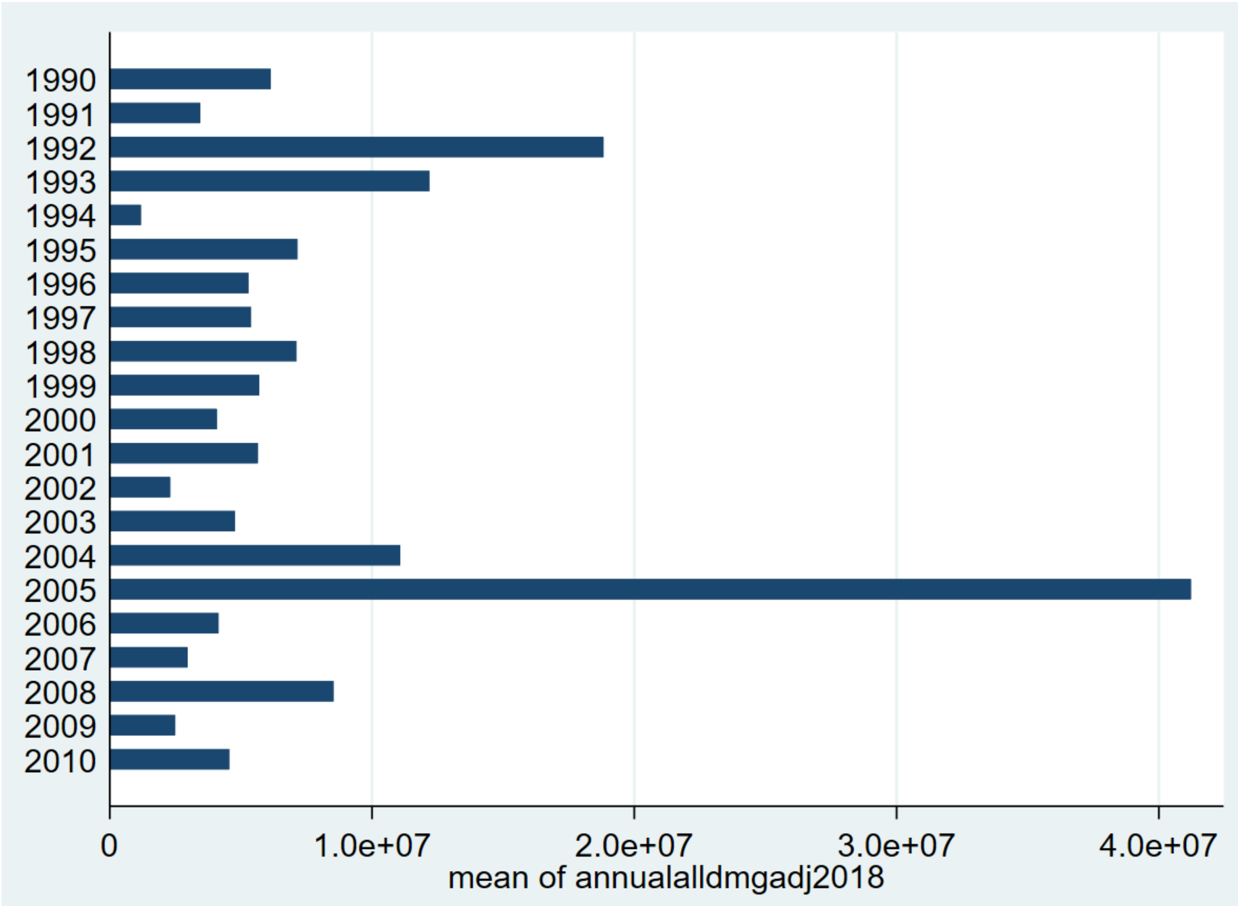

Figure 1.1: Mean of hazard losses

This figure shows a large variation in the size of disaster losses; "annualalldmgadj2018" is the yearly total of property and crop damage in USD summed together. This is data from all hazard types in general. There is a sharp increase for the year 2005, the year of Hurricane Katrina. This raises the question of whether variance in disaster losses is increasing over time.

Table 1.5: Correlation table of flooding losses and weather variables

Pairwise correlations - Flooding

Variables	(1)	(2)	(3)	(4)	(5)
(1) Losses	1.000				
(2) Mean Temp	-0.035*	1.000			
(3) Mean Precip	-0.009	0.458***	1.000		
(4) Global Temp	-0.011	-0.182***	-0.186***	1.000	
(5) Global Precip	-0.006	-0.107***	-0.110***	0.196***	1.000

**** p<0.01, ** p<0.05, * p<0.1*

This correlation table is a pairwise correlation table including only flooding-related losses. The five variables are the same as the ones used in Table 1.1., except for min and max temperature. Of the total of 3,111 counties with nonmissing weather variables, 3,093 counties experienced flooding-related hazards. Mean precipitation has a highly statistically significant positive relationship to mean temperature, as well as the global variables. Generally, the weather variables are strongly correlated with each other. Interestingly, between global and county-level measures, the association was negative; lower global temperature and precipitation predict higher county temperature and precipitation, and vice versa. In terms of the climate variables' effect on flooding losses, mean temperatures on a county level ("Mean Temp") have a very statistically significant negative inverse relationship with flooding losses. This means the lower temperature areas experienced smaller losses. One possible explanation as to why there is a negative correlation is that cooler areas are more susceptible to flooding. Hot areas are dryer, and are therefore less prone to flooding. This is evidence for the hypothesis that temperature predicts flooding events. This coincides with the wet-areas-wetter hypothesis, since wetter climates in the US tend to be cooler. Additionally, the mean temp variable is on the county level, whereas global temp is not. This means that more granular measures of temperature predict losses better than a worldwide measure.

Table 1.6: Correlation table of wildfire losses and weather variables

Pairwise correlations - Wildfires

Variables	(1)	(2)	(3)	(4)	(5)
(1) Losses	1.000				
(2) Mean Temp	-0.004	1.000			
(3) Mean Precip	-0.051***	0.458***	1.000		
(4) Global Temp	-0.004	-0.182***	-0.186***	1.000	
(5) Global Precip	-0.002	-0.107***	-0.110***	0.196***	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 1.8 is a pairwise correlation table consisting of wildfire-related losses and the associated weather variables. Of 3,111 counties, 641 counties experienced wildfire hazards over the 20 year period. The five variables are the same as Table 1.7. However, the significance of the results is different. In this case, mean precipitation was very negatively correlated with losses with a p-value lower than 0.01. Evidently, with less precipitation, wildfires were much more likely to occur. Unlike Table 1.7 which showed evidence of mean temperature having an effect on flooding losses, mean temperature did not have a significant impact on wildfire losses. However, mean temperature does still have a negative relationship with losses. The county-level and global measures of climate also have an inverse relationship here as well. In the table, (2) and (3) have a positive relationship, and (4) and (5) separately are positively correlated.

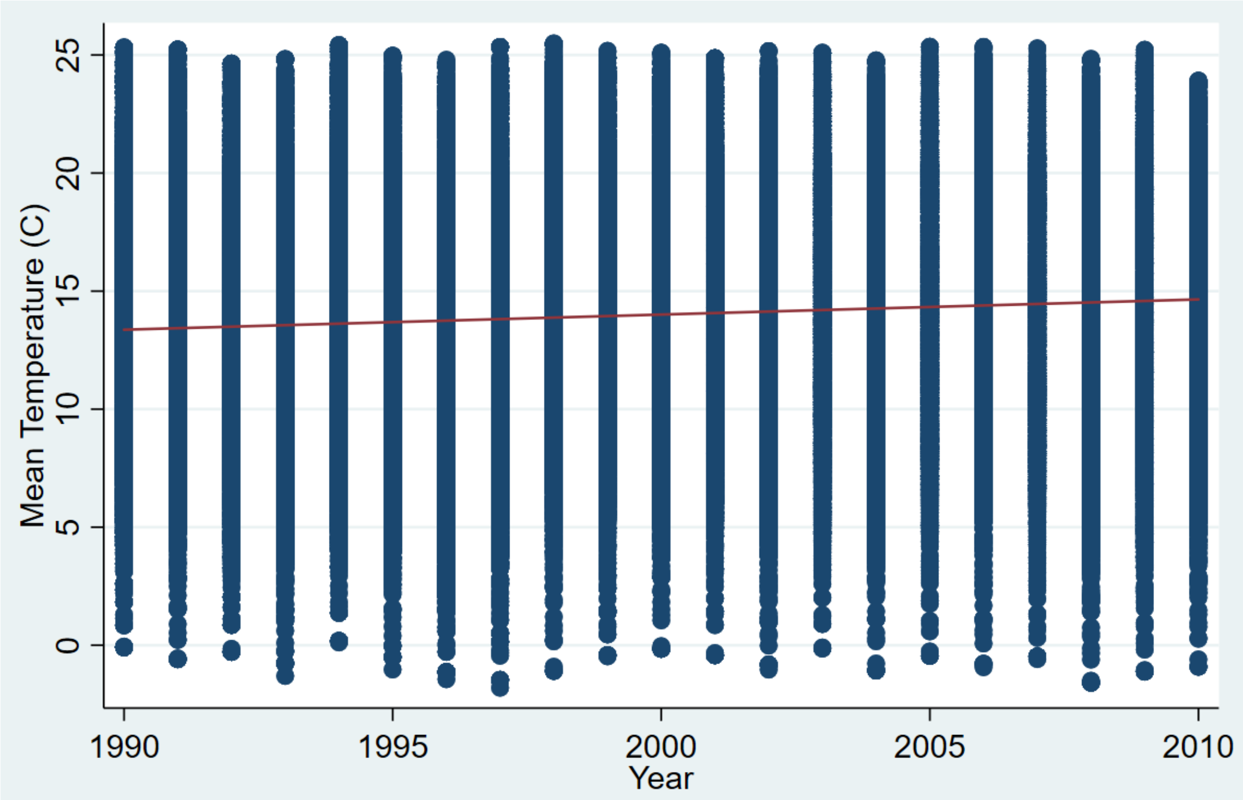

Figure 1.2: Mean Temperatures 1990-2010

In Figure 1.3, temperature is on the Y axis with years on the X axis of the scatterplot. The unit of observation here is county-years. Mean temperatures have slowly increased; the line of best fit has trended upwards, within a range of approximately 13-14 C°. In a separate calculation, rise in average min air temp over 1990-2010 amounted to 0.0121 C°. The rise in average max air temp over 1990-2010 was 0.0381 C°, so average min air temp increased at a slower pace than max air temp.

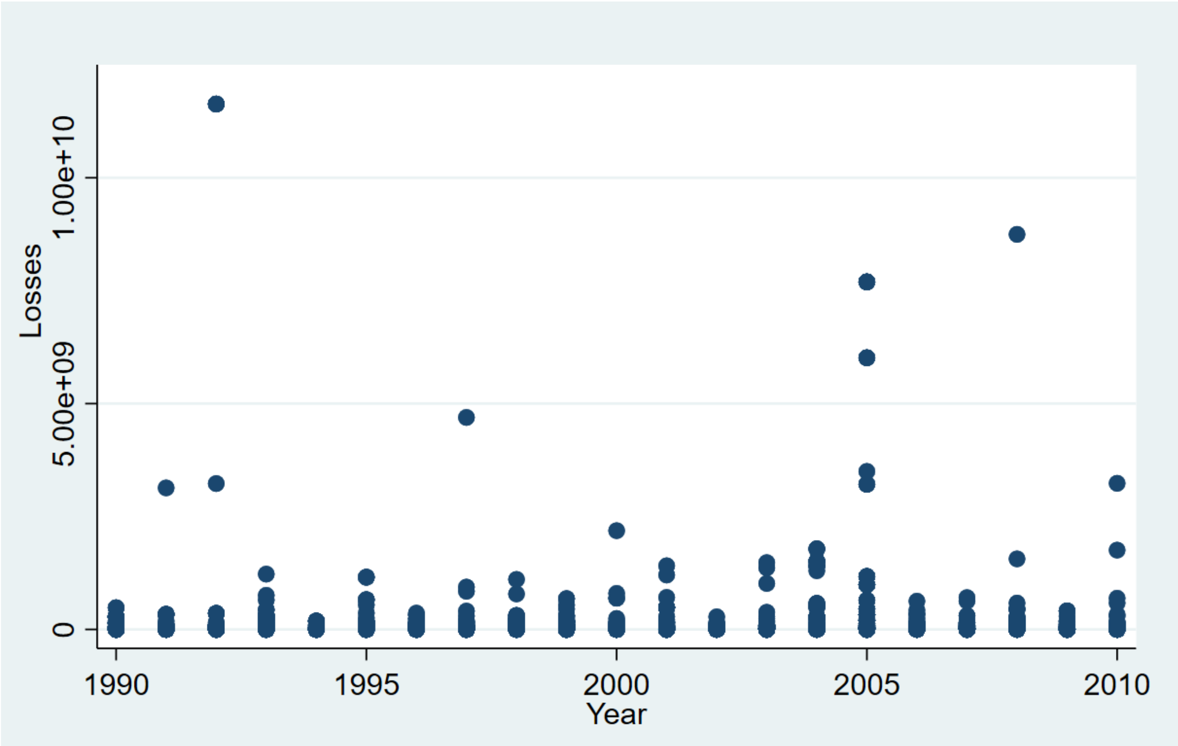

Figure 1.3: Losses 1990-2010

In Figure 1.4, losses are on the Y axis while years are on the Y axis. The unit of observation is county-years. The data points indicating losses have increased in variance which coincides with Figure 1.1 – the points are more scattered as time goes on. Average minimum temperature increased at a slightly higher rate than average maximum temperature.

4. CONCLUSION

I have set out to show quantitative evidence of climate change indicators' impact on disaster losses because of uncertainties in literature as to what extent climate change has impacted disasters. The results demonstrate a variety of effects climate change has on losses. On the county scale, temperature predicts flooding events, while precipitation was found not to have a significant effect on flooding; this contradicts the hypothesis that precipitation would be related to flooding. Some support was found for the wet-areas-wetter hypothesis as the cooler the temperature, the more likely for flooding to occur as seen in Table 1.5. The results also show that lack of precipitation predicts wildfires. However, temperature has comparatively little effect on wildfires, against expectations. The increase in mean temperature leads to the question of how changing mean temperature affects the climate, and in what ways. As mean temperatures have increased, average minimum temperature increased at a higher rate than average maximum temperature. County level measures of weather were shown to have different impacts on losses than global ones.

Regional climate data was expected to be more predictive than global ones, but this was disproven. In the regression seen in Table 1.2, global temperature had a highly significant effect on total losses. Interestingly, the regional and global weather variables used throughout were found to have little correlation to each other. Temperature on a high spatial resolution is extremely valuable in the prediction of disaster losses, but only in certain categories of hazards. This study clarified that global and local measures of climate change are relevant in different applications. As shown in Table 1.2, global temperature does influence losses in general, while location-specific county indicators can reveal more about a specific hazard type. For example, in

Table 1.6, the correlation showed that a lack of precipitation predicts wildfires to a large extent. By using measures on a higher spatial resolution, loss prediction and attribution is more useful when observing hazard types. In the future, it might be prudent to concentrate on certain indicators as they relate to these hazard types, especially considering how strong the link between precipitation and wildfires is.

In terms of implications of this study for future research, the various relationships between variables need to be tested extensively so that attribution studies can use county and global-scale indicators more effectively. NLDAS data on a county level is especially valuable for its predictive power. As disaster losses continue to rise because of increasing temperatures, vulnerability, and exposure, climate change indicators can account for and explain some variation in our climate and allow for prediction of disasters in the future.

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