An analysis of billion-dollar natural disasters in the United States

by

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The student author, whose presentation of the scholarship herein was approved by the program of the study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

I would like to dedicate this thesis to my parents, Dr. Cameron Mackenzie, Alan Gaul, and my friends. Their continuous support, even during difficult times, has made it possible for me to finish this work. I forever would be grateful for their kindness, guidance, and patience.

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NOMENCLATURE

AIC	Akaike Information Criterion
CGE	Computable General Equilibrium
GDP	Gross Domestic Product
I-O	Input-Output
NOAA	National Oceanic and Atmospheric Administration
NCDC	National Climatic Data Center
NWS	National Weather Service
U.S.	United States

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ABSTRACT

The average cost of natural disasters and damage to the U.S. economy has increased each year from approximately $35 billion in 1980 to $300 billion in 2017. This increase in the cost of natural disasters could be due to an increase in the strength and frequency of natural disasters and/or growth in the U.S. economy. This thesis forecasts the cost of natural disasters by fitting probability distributions to the historical cost of billion-dollar disasters. This thesis models the cost of natural disasters based on all weather-related natural disasters that cost more than $1 billion since 1980 and based only on those natural disasters that cost more than $1 billion that occurred in the past 20 years. Using the data from 1980 to 2018, the model forecasts the annual expected cost to be $52 billion. However, if only the recent disaster data is used to fit the model, the expected annual cost $91 billion.

CHAPTER 1. INTRODUCTION

The United States has sustained nearly 250 weather and climate disasters from 1980 to 2018 with a cost of $1 billion or more. The total cost of all the billion-dollar natural disasters in these 38 years exceeds $1.7 trillion [1]. The average cost of billion-dollar natural disasters and damage to the U.S. economy has increased from $35 billion in 1980 to $300 billion in 2017 in real dollars. The frequency of billion-dollar natural disasters has increased by 2.5 times from 1980 to 2018. Twenty billion-dollar disasters occurred in the United States from 1980 to 1985, and 72 billion-dollar natural disasters occurred from 2013 to 2018. Table 1 shows the change in the cost and number of billion-dollar disasters every decade. The recent disasters from 2013-2018 are almost one-third of the total costs of the disaster from 1980 to 2018. 72 out of 244 billion-dollar disasters, nearly 30% of the disaster occurred in the recent five years. All of these costs are adjusted for inflation using the 2018 Consumer Price Index. See [2] for a good review of previous studies that estimate the costs of natural disasters.

Table 1: Number and cost of billion-dollar disasters

Time Period	Number of Billion-Dollar Disasters	Cost	Percent of Total Cost
1980-1989	28	$172 B	10%
1990-1999	52	$268 B	16%
2000-2009	59	$507 B	30%
2010-2018	105	$755 B	44%
Last 5 years (2013-2018)	72	$530 B	31%
Total	244	$1,702 B	100%

The increase in the frequency and costs of billion-dollar disasters could be due to several factors: climate change, increasing population, and increasing economic activity. More than 80% of the nation's total losses from weather and climate events are caused by weather extremes [1]. The real U.S. gross domestic product (GDP) was $6.95 trillion in 1980 and $18.93 trillion in 2018

[3]. GDP increased by more than 172% from 1980 to 2018, but the average cost of billion-dollar disasters increased by more than 750%. The economic cost of natural disasters in the United States has grown faster than the nation's GDP.

Modeling the historical data of billion-dollar disasters can provide an understanding of the past and provide a means to forecast the cost of future disasters. This data could be modeled by time series methods, regression analysis, causal analysis, and simulations.

This thesis uses probabilistic models to forecast billion-dollar disasters in the future. Simulating the extreme events with a mathematical model might provide a better understanding of the billion-dollar disasters. The billion-dollar weather and climate natural disasters are recorded and published by the National Oceanic and Atmospheric Administration (NOAA) [1]. NOAA categorizes these disasters into seven types: drought, flood, freeze, severe storm, tropical cyclone, wildfire, and winter storm. This thesis model each type of disaster separately and fits a probability distribution for the frequency and the cost for each type of disaster. Table 2 depicts the cost and percentage impact of the billion-dollar disasters. The costs of disasters are unevenly spread for each type of disaster and split into unequal percentages. We simulate each type of disaster and combine the simulation of each type of disaster to generate an annual cost of billion-dollar disasters in the United States.

Fitting probability distributions to all the data from 1980 to 2018 assumes that the frequency and costs of these disasters have remained constant in the preceding 38 years. Since that might be an unrealistic assumption, we also fit probability distributions to only the most recent data for each type of disaster (approximately twenty years' worth of data). Over the past 38 years, the United States' GDP has also changed over time and went through a number of recessions and economic boom [4]. This might have an effect on the cost of disasters. We also model the impact of GDP on costs of natural disasters separately. This thesis presents the simulated results to give a broader picture of the risk that the United States can face from natural disasters, which cost more than a billion dollars. A probabilistic forecast of billion-dollar disasters' costs provides better insights than a deterministic model into the risks. Policymakers can use these types of models to develop strategies and allocate resources to prepare for these large-scale disasters.

Table 2: Cost of each disaster type

Disaster Type	Number Events	Cost	Percent of Total Cost
Freeze	9	\$30 B	2%
Tropical Cyclone	42	\$935 B	55%
Winter Storm	17	\$49 B	3%
Drought	26	\$248 B	15%
Wildfire	16	\$80 B	5%
Severe Storm	105	\$233 B	14%
Flooding	29	\$126 B	7%
Total	244	\$1,702 B	100%

This thesis is divided into five sections. Chapter 2 identifies the open questions from the past work done by many authors. Chapter 3 presents the methodology and the steps taken to model the billion-dollar disasters. The analysis includes five models to estimate the cost to the U.S. economy. Two of the five models measure the effect of the GDP of the U.S into account. One model compares the results to validate the best model. Chapter 4 discusses the outcomes of fitting distributions to the data and running the Monte Carlo simulation [5]. The discussion highlights the risk of natural disasters expressed in costs to understand the benefits of increasing the country's preparedness for natural disasters and enhancing the nation's resilience.

CHAPTER 2. LITERATURE REVIEW

A number of studies have estimated the economic impact of natural disasters. Some of the most common models to estimate the economic losses are the Input-Output (I-O) and the Computable General Equilibrium (CGE) models [6]. These models consider the economy as a collection of a small industry that interacts with each other through intermediate consumption. Models are generated to fit the specific scenarios to measure the reduction in the GDP in areas impacted by the disruptions to predict the impacts of disasters inter regionally [7]. Some authors have even attempted to isolate parts of the state of California [8] and its ripple impact on the rest of the U.S. economy. In general, these models identify the direct and indirect losses with an aim to account for as many variables as possible [9]–[11]. These models are as good as the assumptions of the model to estimate the economic impacts and prone to changes as the new data emerges. Al Kazimi and MacKenzie [2] review several I-O and C.G.E. studies of past and potential disasters in the United States.

The National Weather Service (NWS) provides weather-related products and services to the public. N.W.S. has maintained a historical database from flood damage across the nation since 1870. The accuracy of these flood datasets has been tested and shown to be consistent but not perfect [12]. These errors in data arise while collecting and estimating the economic impact due to various reasons. The error could be a combination of many variables, including incompatibility between different sources, human error, change in population, change in wealth or development of the area, and extreme weather disasters offsetting the overall results. In the 1980s, NOAA's National Climatic Data Center (NCDC) started tracking U.S. weather and climate events which individually cost at least $1 billion in overall damages and costs [13]. The data at NCDC is available to the public. The data collected by NCDC relies on the insurance companies and the government agencies. Researchers have identified new approaches to quantify the uncertainty in this data source as well [14].

The billion-dollar disaster weather data published by NOAA and used in this thesis likely underestimate losses by 10-15% [15]. This implies that the cost of the billion-dollar disasters is actually more than what is listed. The interdependence of economic activity is difficult to measure. The data on losses from natural disasters contains significant amounts of uncertainty [16], and the full extent of material losses may not be known until several years after the disaster. The cost of some disasters might also be overestimated in the long term. For example, rain from a hurricane might be beneficial to the agriculture crops, and the local construction required to replace the old facilities could help grow the GDP in the long term following a severe disaster [13]. Smith and Matthews [14] construct a confidence interval around the billion-dollar disasters dataset. Probability distributions provide the average time period or frequency of disasters. After any natural disaster, government agencies, institutions, and insurance companies publish their estimate of the cost of the disaster. These estimations use various methodologies and a data collection approach. Different types of methodologies lead to different estimations. One study finds that the estimation differs by a factor of 2 or more for more than 50% of the flood damages in California that cost less than $50 million [12]. As the area or the period of time is extended, the underestimation and overestimations errors tend to average out. The errors are significantly less for events that cost more than $500 million. The losses from crop damage and flood loss cause the major climate extremes loss [17]. Crop yield values have increased almost by 50% from the year 1980 to 2000; this in turn has increased the GDP of the nation.

General conclusions may be difficult to evaluate about the weather phenomena such as tornadoes, hail, and thunderstorms because the observational evidence for changes is too broad and scattered across places [18]]. Evidence exists that the frequency of heavy precipitation events and the frequencies and intensities of tropical cyclones and hurricanes [19], [20] have increased in North America. A probabilistic event attribution framework by Pall [21] concludes that the risk of flood occurrence in the U.K. in the year 2000 substantially increased due to anthropogenic greenhouse gas emissions. In 1993 in American Midwest, approximately 3.3 million ha of soybean and corn fields were flooded, causing a 50% decrease in corn yields in Iowa, Minnesota, and Missouri and a 20–30% decrease in three other states [22]. Flood also significantly damaged transportation infrastructure.

There have been a number of disastrous floods in the last two decades. Recent studies on past and current changes of precipitation extremes in North America have reported an increasing trend in precipitation over the last half-century [20]. A study [23] constructed regression relationships between annual flood loss and socio-economic and climate drivers, with a conclusion that a 1% increase in average annual precipitation would lead to an increase in annual national flood loss of around 6.5%. However, the conclusions are highly dependent on the methodology.

As the world has also become wealthier during the past decades [24], the costs of natural disasters have also increased. The flood losses have greatly increased, mainly driven by the expanding assets at risk [25]. However, not all people are equally impacted by the disasters. Low-income populations are more vulnerable, physically and psychologically, to natural disasters [26], and better data is needed to assess the impact of disasters on the population with different socio-economic statuses. The public perception also changes with the amount of accurate information they receive from the trusted weather and climate agencies [27]. Having accurate forecasts benefits society in making a range of decisions valuable for their well-being. Even as the scientific understanding of the economic consequences of these extreme events improves, higher-quality data is required to fully understand their economic costs across years, events, and places [28]. As the data become abundant, the mathematical models can further be extended into multi-event disaster planning to quantify resilience and improve decision making [29]. Policymakers can use these mathematical models to make more effective decisions to mitigate the consequences of natural disaster.

Extreme events continue to take a toll on the nation, threatening the well-being of Americans. Quantitative investigations of historical trends provide better results in estimating the frequency and losses from natural disasters [30]. The National Research Council report on natural disasters recommended risk-based approaches to resilience [31]. However, there is no study using a probabilistic approach for tracking the risk of extreme events using the current data [26]. There is a need for mathematical models, improved data, and probabilistic approaches in response to natural disaster anticipation.

CHAPTER 3. METHOD

NOAA annually records and publishes natural disasters whose cost exceeds $1 billion. Figure 1 shows substantial variation from year to year in the costs of billion-dollar disasters from 1980 to 2018. As seen in Figure 1, the total cost of all disasters in 2005, 2011, and 2017 are significantly higher than in the other years. This is largely due to a few extreme events. The total cost of $221 billion dollars in 2005 is largely due to Hurricane Katrina. The high cost in 2011 is due to Hurricane Irene. Several droughts, Hurricane Harvey, and Hurricane Maria generated high costs in 2017. We initially attempted to fit a probability distribution to this entire data set, but no distribution fits well to the observed data or provided good forecasts.

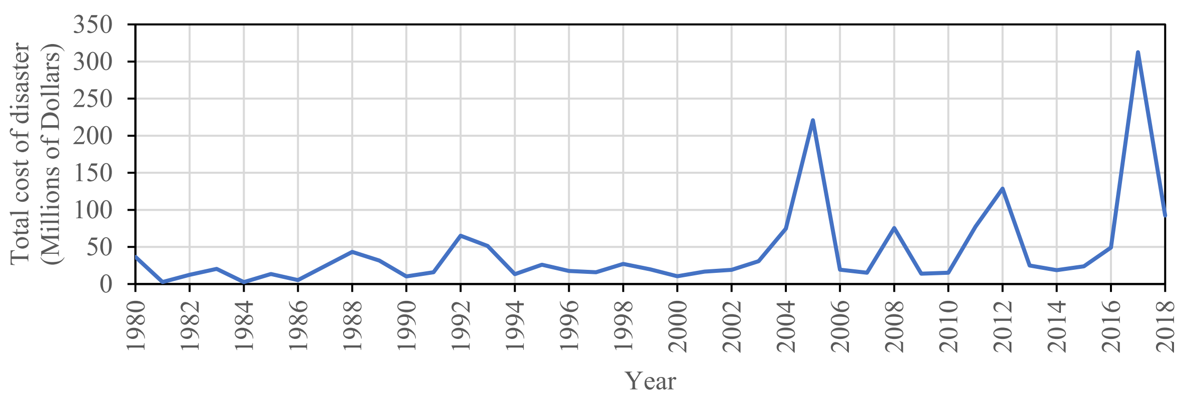


Figure 1: Total cost of billion-dollar natural disasters from the year 1980 up to the year 2018

A better approach than fitting a model to all of the data is to fit separate models for each disaster type. Analyzing each type of disaster also provides a better understanding of these billion-dollar disasters. Modeling each type of disaster separately can make the model more robust to changes in the data. Using probabilistic models rather than deterministic models reflects the uncertainty that is inherent in forecasting future economic costs from natural disasters.

We use the billion-dollar disaster data for each type of disaster. We model the distributions of each type of billion-dollar natural disaster separately: drought, flood, freeze, severe storm (i.e., tornado, hail, wind damage), tropical cyclone, wildfire, and winter storm. First, we fit a discrete distribution to the annual frequency of each type of disaster. This analysis also tests to see if the frequency of any of these disasters is correlated. If the frequencies are highly correlated, the model will incorporate this correlation. Second, we fit a continuous probability distribution to the cost of each type of billion-dollar disaster. We assume the cost for each type of a billion-dollar disaster is identically and independently distributed. We use the Akaike information criterion (AIC) [32] and the log-likelihood [5] to assess the goodness of fit and choose a distribution. We also attempt to use common distributions across many of the disasters. If a single distribution performs very well according to the AIC. and log-likelihood metrics for many different disasters, we attempt to use that same distribution for each type of disaster.

JMP Statistical Software is used to fit a continuous random variable for the cost of each type of disaster. We fit the costs for each type of disaster to the following continuous distributions: Johnson with a lower bound, sinh-arcsinh (SHASH), lognormal, generalized log, gamma, normal mixtures (2 and 3), Weibull, extreme value, exponential, and normal. Five distinct models are created, and each model uses a different dataset to analyze the economic impact of these natural disasters.

Model 1 uses all the historical data from 1980 to 2018 to model the costs of natural disasters. We start with using all of the data to fit the discrete distribution to the annual frequency. This frequency is analyzed and incorporated into the model to generate the number of disasters that occur in a year for each of the seven types of disasters separately. The probability distribution is fit to the cost of each type of disaster for all the disasters that cost more than $1 billion from 1980 to 2018. The AIC and log-likelihood values are evaluated, and the best fit of the probability distribution is selected for each type of disaster. Monte Carlo simulation is used to generate the frequency of disasters and their costs for all seven disasters. The simulated cost is summed up to obtain the total cost of disasters from the events that cost more than a billion-dollar to the U.S. economy.

Model 2 follows the same steps as Model 1 with one crucial difference—Model 2 only uses the most recent disaster data as opposed to using all of the data from 1980 to 2018 as in Model 1. Figure 2 depicts the number of each billion-dollar disaster by year. The number of billion-dollar disasters seems to increase a lot beginning in 2000. In Model 2, we examine each disaster separately and identify a year in which the annual frequency of the disaster appears to change. After identifying the year in which the annual frequency changes, we follow all of the steps in the previous paragraph to fit a probability distribution for the frequency and the cost for each type of disaster, but we only use the data from the more recent year through 2018 to fit these distributions.

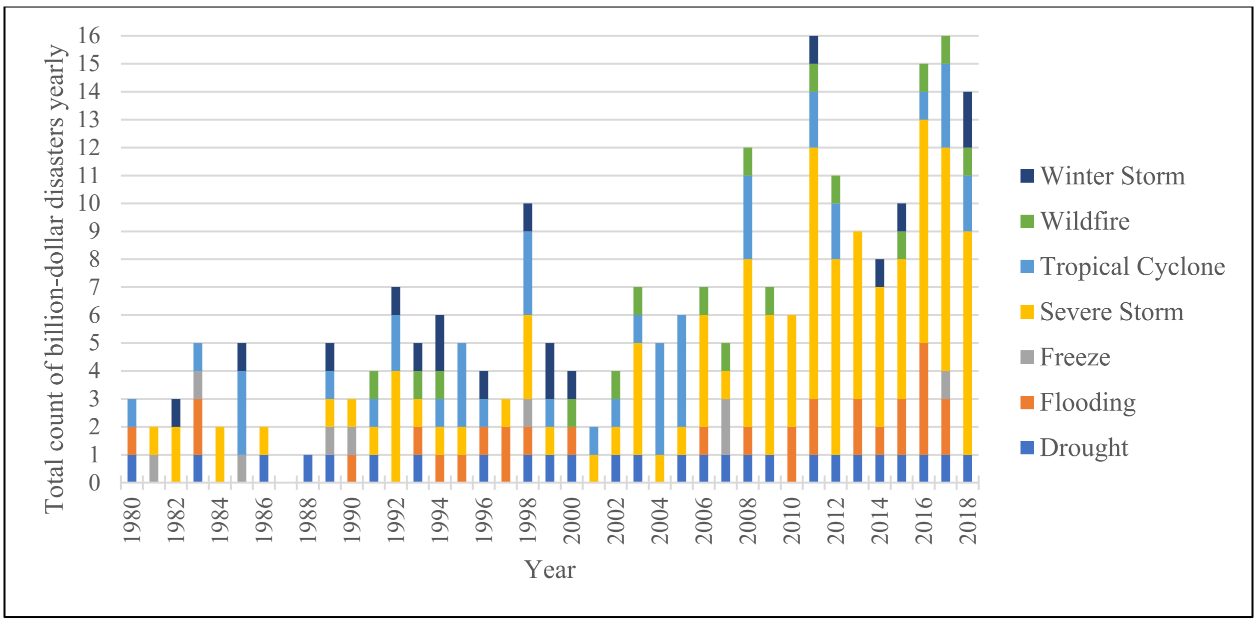


Figure 2: Frequency of each type of billion-dollar natural disasters from 1980-2018

One explanation for the growth in billion-dollar disasters and the increase in costs from 1980-2018 may be the growth of GDP and population in the United States. Accounting for the change in wealth and population in the United States within the model may provide a better forecast of the financial costs of natural disasters. Although the costs of natural disasters are adjusted for inflation via the 2018 Consumer Price Index, we want to account for GDP as well. Model 3 uses the same data for the cost of disasters as Model 1 (years 1980-2018) and divides the costs by the corresponding GDP of that year. We use the same steps as Model 1, but the costs of disasters are replaced by the ratio of the cost of the disaster to GDP We generate the ratio of cost of disasters to the GDP using Monte Carlo simulation and multiply simulated annual costs for each disaster and the GDP in 2018 to generate a probabilistic estimate of the cost of natural disasters.

Model 4 combines the process of Model 2 and Model 3. We use the ratio of the cost of the disaster to the corresponding GDP Rather than using all of the data from 1980-2018; we only use the recent disaster data similar to Model 2. This creates another dataset with the same number of billion-dollar disaster events as Model 2. We follow identical steps to Model 3 to generate the annual costs and multiply the annual costs by the GDP in 2018.

Model 5 follows a similar process as Model 2. Instead of modeling cost after the year 2000, in which the annual frequency of the disaster appears to change. We model from 1980 to a year prior to the year used in Model 2. We follow all the steps as in Model 2 to fit the distribution to frequency and cost for each type of disaster.

A single trial in the Monte Carlo simulation begins by randomly generating the number of billion-dollar disasters that occur in a single year for each of the seven disasters. For each simulated disaster, we randomly generate the cost of that disaster from the probability distribution that best fits that type of disaster. If the cost of disaster generated in a trial is negative, we generate another cost of that disaster from the probability distribution until the cost is positive. The U.S. GDP in 2018 was $18.93 trillion. As mentioned previously, for Model 3 and Model 4, to convert the ratio of data to the GDP back to the costs of disasters, we multiply the costs generated by the model for each type of disaster and the GDP in 2018. We calculate the total cost of billion-dollar disasters in a single trial by summing the costs of individual disasters. This process is repeated 100,000 times to generate a simulated probability distribution of the annual costs of billion-dollar disasters. The annual costs for each of the seven types of disasters and the total annual costs from all the disasters are analyzed and presented in Chapter 4.

CHAPTER 4. RESULT

4.1 Fitting Distributions

This thesis analyzes, fits distributions, and simulates all the billion-dollar natural disasters in the U.S. economy from 1980 to 2018. When all the data is included (Models 1 and 3), the annual frequencies of drought and wildfire have a correlation equal to 0.43, and the annual frequencies of flood and severe storm have a correlation equal to 0.48. These are the only two correlations greater than 0.4. It is reasonable that these disasters are correlated because hot and dry weather can lead to more droughts and wildfires, and rainy weather can lead to more severe storms and floods. If just the recent disasters are analyzed (Models 2 and 4), the correlation between droughts and wildfires increases to 0.64, and the correlation between floods and severe storms is 0.37. Four models incorporate the correlation between drought and wildfire and between flood and severe storm so that the simulated number of disasters for these four types of disasters exhibit these correlations. The annual frequency of each of the other three disasters (freeze, tropical cyclone, and winter storm) is treated as independent of the frequency of the other types of disasters.

Table 3 depicts the distribution for the annual frequency for each distribution, the year in which data for Model 2 and Model 4 begins (i.e., the year in which the annual frequency changes), and the parameters for each distribution for the four models. These parameters are based on the data visualized in Figure 2. The Poisson distribution is used to model the number of events for freeze, tropical cyclone, winter storm, severe storm, and flood. The parameter λ (average number of annual events) for the Poisson distribution is given in Table 3 for these disasters. The number of droughts or wildfires never exceeded 1 in any given year from 1980 to 2018, and the frequency of each of these two disasters is modeled as a Bernoulli random variable with the probability p. The annual frequency of all the disasters except for freeze increases, and the year in which the annual frequency changes are depicted in Table 3. Since the annual frequency of freeze appears to remain constant, we use the data for freeze from 1980 to 2018 in the five models.

Table 3: Distributions on the annual frequency

Disaster type	Type of distribution	Model 1 & 3 parameter	Year Model 2 & 4 begins	Model 2 & 4 parameter
Freeze	Poisson	$\lambda = 0.23$	1980	$\lambda = 0.23$
Tropical cyclone	Poisson	$\lambda = 1.07$	2004	$\lambda = 1.4$
Winter storm	Poisson	$\lambda = 0.44$	2009	$\lambda = 0.5$
Drought	Bernoulli, correlated with wildfire	$p = 0.67$	2000	$p = 0.84$
Wildfire	Bernoulli, correlated with drought	$p = 0.41$	2000	$p = 0.68$
Severe storm	Poisson, correlated with flood	$\lambda = 2.7$	2006	$\lambda = 5.85$
Flood	Poisson, correlated with severe storm	$\lambda = 0.74$	2006	$\lambda = 1.3$

Fitted probability distributions are generated using the frequency of the type of disaster for each model. Table 4 shows the log-likelihood and AIC for the distributions for the severe storm based on JMP. The Johnson distribution (with a lower bound) fits the best to the historical data of severe storms among all the other distributions. Figure 3 provides an example of fitting the Johnson distribution to the costs of severe storms from 1980-2018. The SHASH distribution's AIC and log-likelihood values are very similar to that of the Johnson distribution. The two distributions look very similar and using either of these two distributions to model the costs of severe storms is reasonable. The Johnson distribution perhaps underestimates the likelihood of extreme costs, and three severe storms cost more than $9 billion, which the Johnson distribution has trouble capturing. Despite this deficiency, the Johnson distribution provides a good fit for every type of disaster except for the costs of recent winter storms. We prefer to use the same type of distribution for as many disasters as possible, and we select the Johnson distribution to model the cost of each type of disaster except for winter storm in Model 2. The AIC and log-likelihood values for the Johnson distribution remain within 10 to the best distribution for each type of disaster in four models, except for winter storm and drought. For winter storm, the AIC value of Weibull distribution is 79.5 while the AIC value of Johnson distribution is 109.6. The Weibull distribution provides the best fit for the recent winter storm cost in Model 2 and Model 4. Table 5 displays the probability distributions used for each of the models and disaster type.

Table 4: Distributions comparison for severe storms, 1980-2018

Distribution	-2*Log-Likelihood	AIC
Johnson	1680	1688
SHASH	1682	1691
Lognormal	1735	1739
Generalized log	1735	1741
Gamma	1766	1770
Normal 2 mixture	1762	1772
Normal 3 mixture	1762	1779
Weibull	1793	1797
Extreme value	1793	1797
Exponential	1828	1830
Normal	1861	1865

Table 5: Type of probability distributions for each of the four models

Disaster type	Model 1	Model 2	Model 3	Model 4
Freeze	Johnson	Johnson	Johnson	Johnson
Tropical cyclone	Johnson	Johnson	Johnson	Johnson
Winter storm	Johnson	Weibull	Johnson	Weibull
Drought	Johnson	Johnson	Johnson	Weibull
Wildfire	Johnson	Johnson	Johnson	Johnson
Severe storm	Johnson	Johnson	Johnson	Johnson
Flood	Johnson	Johnson	Johnson	Johnson

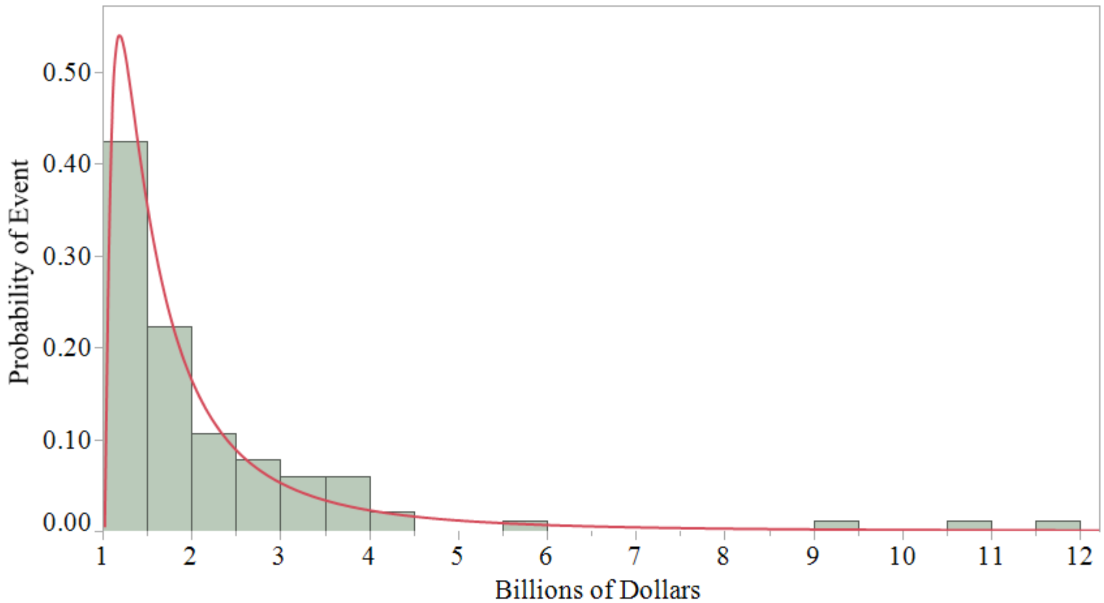


Figure 3: Fitted Johnson distribution to severe storm dollar value during the period 1980-2018

4.2 Simulating economic costs

As mentioned, 100,000 simulations are generated for each of the five models. Figure 4 shows the cumulative probability of the annual costs for each model. According to Model 1, which is based on all of the data from 1980 to 2018, the expected cost of all disasters is \$52 billion with a standard deviation of \$95 billion. The median annual cost is about \$30 billion. There is a 10% chance that the cost of billion-dollar disasters will exceed \$100 billion and about a 5% chance that the cost will exceed even \$150 billion. The vast majority of the simulations result in costs less than \$80 billion. However, some simulations result in costs of \$200, \$300, or even \$400 billion. As seen from Figure 4, the likelihood of costs exceeding \$300 billion is very small, however. Model 1 suggests that the United States should plan for \$20-\$100 billion in economic losses from these large-scale natural disasters, but the losses could be as large as \$200 to \$300 billion.

Model 2, which is based on the most recent data, results in an expected cost of \$91 billion with a standard deviation of \$120 billion. The median annual cost is \$56 billion, almost twice the value from Model 1. There is a 10% chance that the economic costs will exceed $175 billion in a single year. The annual cost of disasters based on using just the recent data is almost twice the annual cost based on using all of the data in Model 1. This increase in cost is due to increased frequency of natural disasters and the increase in costs of these billion-dollar disasters over the past two decades. Model 2 suggests that the United States should plan for about $40-$175 billion in economic costs from billion-dollar natural disasters with losses that could be as large as $300 or even $400 billion. These extreme costs represented more than 2% of U.S. GDP in 2018.

Models 3 and 4 simulate the ratio of annual costs to GDP and multiply the resulting cost by U.S. GDP in 2019. Model 3, which uses all the data from 1980 to 2018, generates higher annual costs than those in Model 1. The median cost of disasters estimated by Model 3 is $40 billion. For Model 3, which has a similar dataset of costs of disasters as Model 1 from 1980 to 2018, the expected cost is $91 billion, approximately $26 billion higher than Model 1. Model 3 has a standard deviation of $220 billion, which is twice the amount of standard deviation from Model 1. The probability of exceeding $100 billion is 20%, which is also twice as large as Model 1. As seen from Figure 4, Model 3 predicts the costs can exceed even $400 billion.

Model 4 relies on the same recent data as Model 2 while simulating the ratio of cost to GDP. The expected cost generated by Model 4 is approximately $108 billion with a standard deviation of $321 billion. The median annual cost is $62 billion. There is a 30% chance that the annual cost will exceed $100 billion and a 10% chance the annual cost will exceed $200 billion.

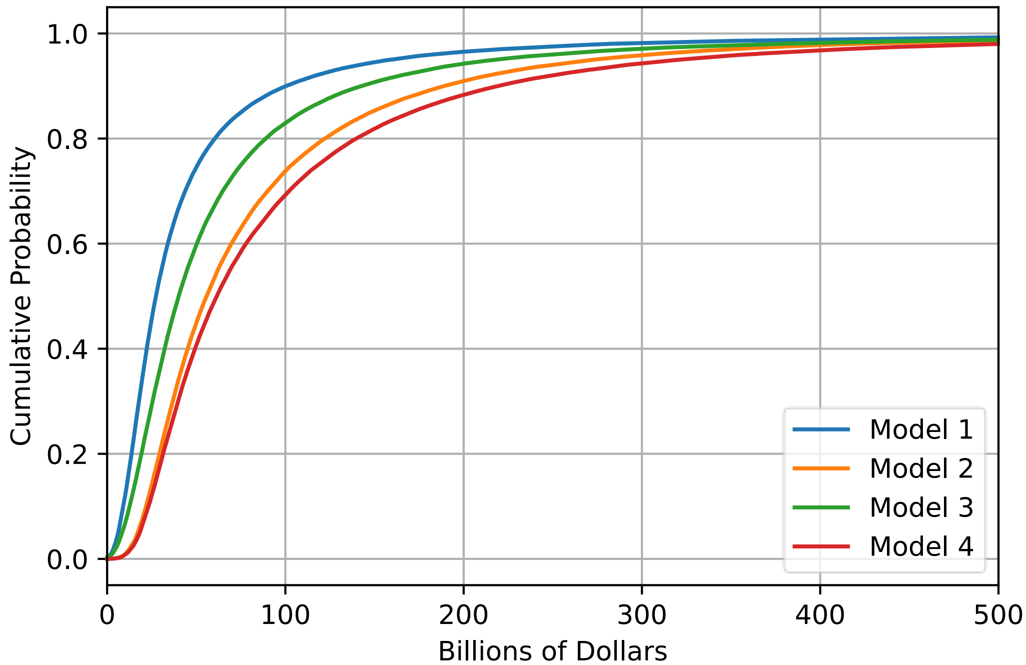


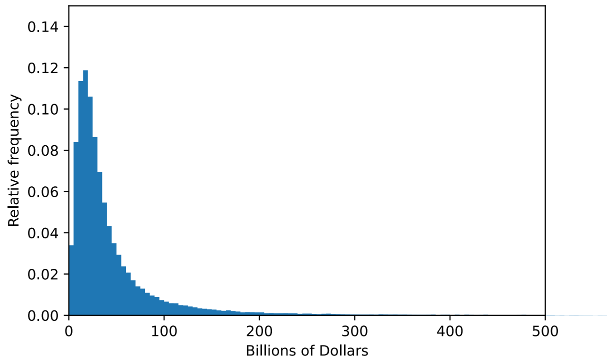
Figure 4: Risk curves generated by the four models

Table 6 presents the simulated annual costs for each of the seven types of disasters. The 99th percentile is depicted in order to show the very extreme or 1-in-100-year scenario. Since none of the disasters are perfectly correlated to each other, as shown in Table 3, the sum of the 99^{th} percentile of each type of disaster will not be equal to the 99^{th} percentile of the total cost. The 99^{th} percentile of the total costs is calculated separately from the models and presented in Table 6. Tropical cyclones are the largest contributor to the total cost of disasters, and they account for 50-80% of the average total cost in the four models. Model 2 shows a 90% increase in tropical cyclones' cost than Model 1, which signifies the substantial economic impact of tropical cyclones in recent years. Severe storms occur more frequently than any other disaster, but the total costs due to severe storms are much less than tropical cyclones. Recent disaster data depicts that the cost and frequency of severe storms are also growing. Winter storm is the least expensive disaster among all the seven types of weather and climate disasters, and the average cost of winter storms is always less than 3% of the total average cost for the four models.

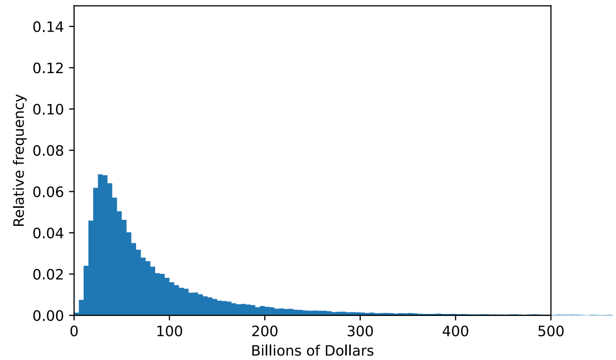
Table 6: Costs in billions of dollars for each type of disaster generated by the four models

Disaster type	Model 1		Model 2		Model 3		Model 4	
	Average	**99-percentile**	**Average**	**99-percentile**	**Average**	**99-percentile**	**Average**	**99-percentile**
Freeze	$0.8 B	$8 B	$0.8 B	$8 B	$2 B	$19 B	$2 B	$19 B
Tropical cyclone	$32 B	$399 B	$61 B	$534 B	$37 B	$410 B	$68 B	$579 B
Winter storm	$1 B	$12 B	$1 B	$7 B	$2 B	$20 B	$1 B	$7 B
Drought	$6 B	$53 B	$7 B	$41 B	$11 B	$109 B	$5 B	$15 B
Wildfire	$3 B	$34 B	$4 B	$45 B	$13 B	$124 B	$12 B	$142 B
Severe Storm	$6 B	$22 B	$13 B	$36 B	$8 B	$27 B	$15 B	$43 B
Flood	$3 B	$27 B	$4 B	$27 B	$5 B	$47 B	$5 B	$30 B
Total annual cost	$52 B	$425 B	$91 B	$565 B	$78 B	$548 B	$108 B	$681 B

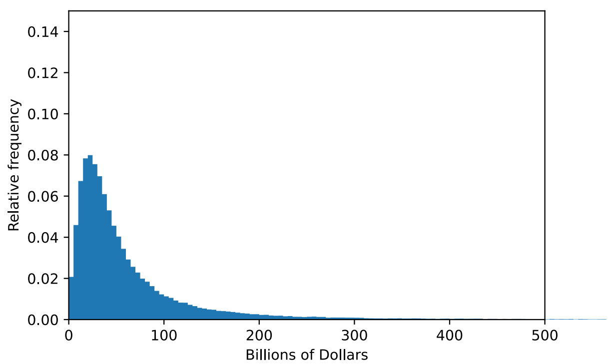
Figure 5 shows a relative frequency histogram of the simulated annual costs for all billion-dollar disasters for the four models. The annual cost generated by the four models is highly skewed to the right and unimodal. We create equally spaced bins for the four models, width of each bin represents $5 billion. The major proportion of the values falls under $100 billion for the four models. Models 3 and 4 show significant right-hand skewness with relatively fat tails and higher number of events costing more than $100 billion. Incorporating GDP into the models appears to result in larger forecasts of the costs of disasters.



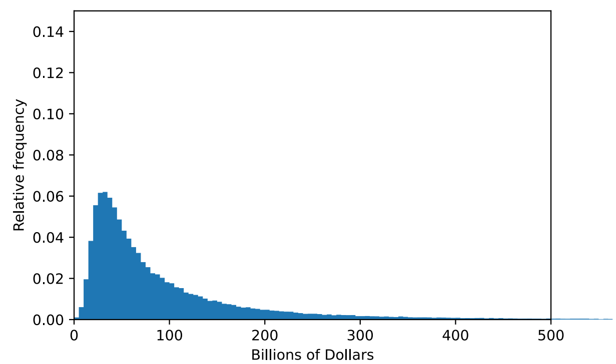
5a – Model 1



5b – Model 2



5c – Model 3

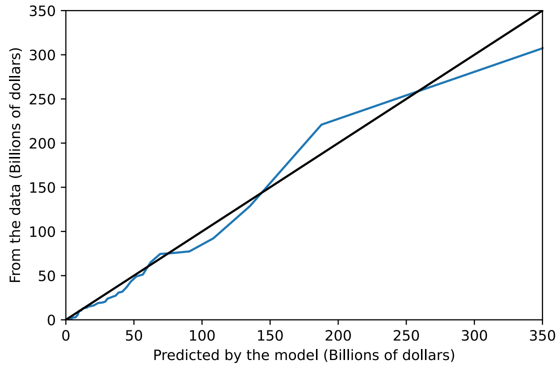


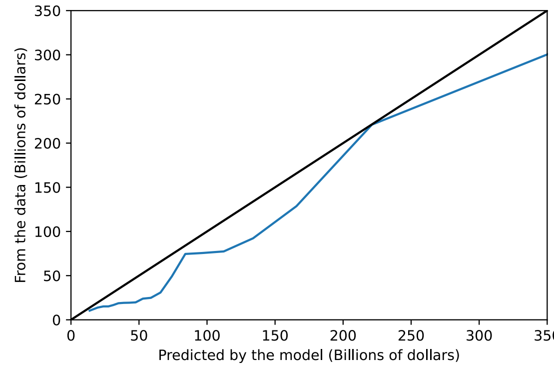
5d – Model 4

Figure 5: Relative frequency histogram of annual costs of disasters by each of the model

Quantile-quantile (Q-Q) plots provide a means to analyze how well the simulated results match the data. Figure 6 shows the Q-Q plots for the four models. The actual annual cost from the data is plotted on the y-axis versus the simulated annual cost on the x-axis. Figures 6a and 6c show the models which use all the data from 1980-2018, whereas in Figures 6b and 6d use the yearly data from 2000-2018. Figures 6b-6d demonstrate that their corresponding models may overestimate the actual costs since the plotted points are to the right of the 45-degree line. In Figure 6a, the plotted points lay much more consistently along the 45-degree line. Q-Q plots for Models

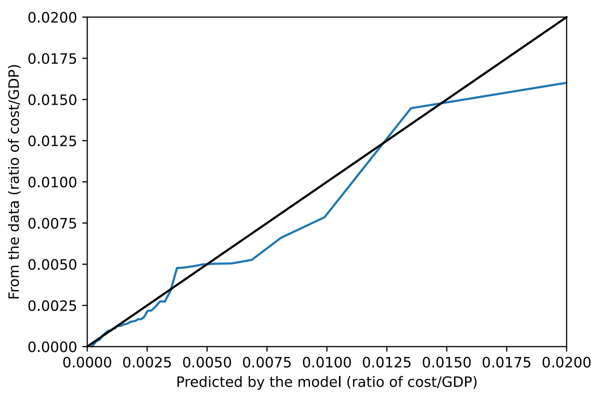
3 and 4 are calculated by multiplying the ratio by the 2018 GDP Since the Q-Q plots use the data from years prior to 2018, multiplying the ratio by the 2018 GDP likely influences these larger forecasts from the simulated models.

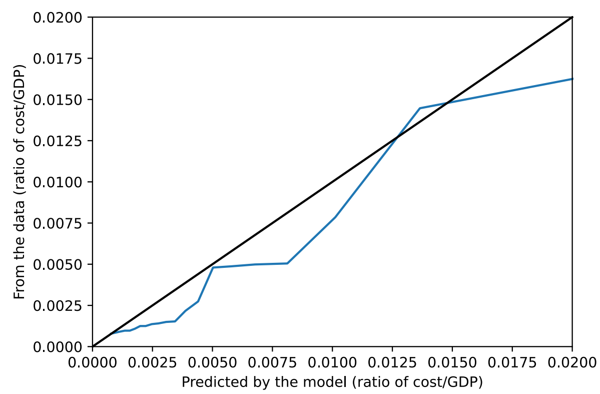




6a – Model 1

6b – Model 2





6c – Model 3

6d – Model 4

Figure 6: Q-Q probability plot of the annual cost of disaster for each of the models

4.3 Comparison between 1980-2000 & 2000-2018

The statistical forecasting of this work is based on the assumption that the cost of each type of disaster is independent and identically distributed. This makes the models time independent or time stationary. However, the statistical properties of the cost of disasters such as mean, variance, and correlations are not constant and have been increasing over time [32]. We compare the results from Model 2 with a new model (Model 5). Model 5 uses the costs and frequency of each type of disaster from 1980 to a year prior to the year used in Model 2, as shown in Table 3. The annual expected cost generated by Model 5 is approximately $24 billion, with a median of $14 billion and a standard deviation of $43 billion. Figure 7 shows the relative frequency histogram of annual costs of billion-dollar disasters generated by Model 5. The extreme losses in Model 5 are less expensive than Model 2, and Model 5 contains many more disasters less than $30 billion compared to Model 2.

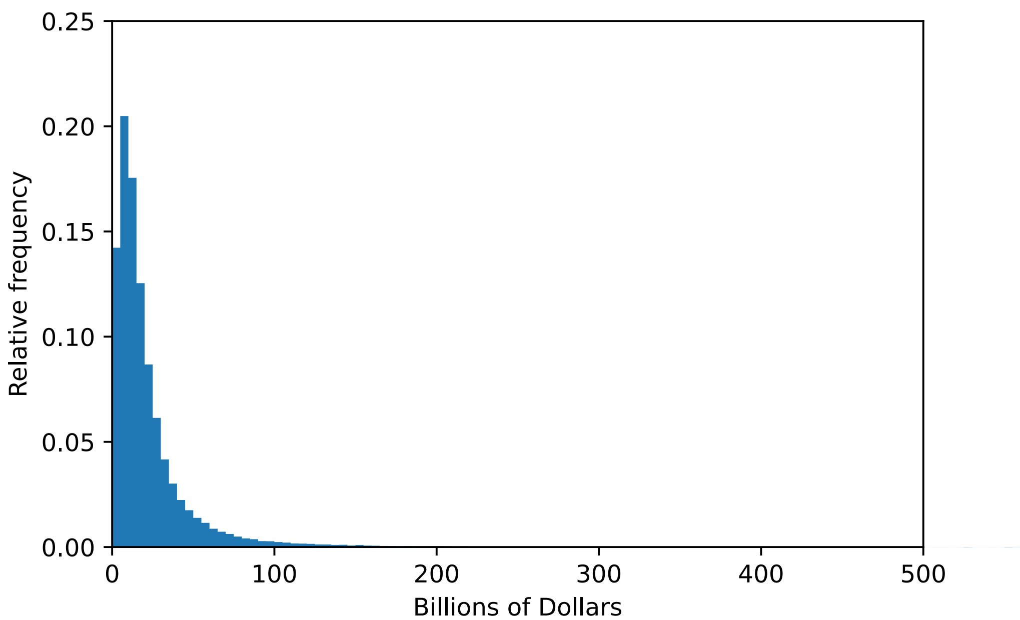


Figure 7: Relative frequency histogram of annual costs of disasters from 1980-2000 of Model 5

Table 7 shows the average expected cost of each type of disaster and 99-percentile values for Model 5 and Model 2. The disasters freeze, winter storm, drought, and flood have the same average cost in both Models 2 and 5, and the 99-percentile values for these disasters in Model 5 are either equal to or slightly greater than the 99-percentile values of the same disaster in Model 2. This suggests that the billion-dollar disasters of freeze, winter storm, drought, and flood have not become more frequent or damaging in the 2000s. The cost of tropical cyclones, wildfires, and severe storms are much greater in Model 2 than in Model 5. The average cost of tropical cyclones is 7.6 times larger in Model 2 than Model 5 ($61 billion compared to $8 billion); the average cost of wildfires is 8 times larger in Model 2 than Model 5 ($4 billion compared to $0.5 billion); and the average cost of severe storms is 4.3 times larger in Model 2 than Model 5 ($13 billion compared to $3 billion). The 99-percentile costs of these three disasters are substantially greater in Model 2 than in Model 5. This result suggests that tropical cyclones, wildfires, and severe storms have greatly increased in frequency and/or severity in the 2000s.

Table 7: Cost generated in billions of dollars for each type of disasters by Model 5

Disaster type	**Model 5**		**Model 2**	
	Average	**99-percentile**	**Average**	**99-percentile**
Freeze	$0.8 B	$8 B	$0.8 B	$8 B
Tropical cyclone	$8 B	$84 B	$61 B	$534 B
Winter storm	$1 B	$11 B	$1 B	$7 B
Drought	$7 B	$86 B	$7 B	$41 B
Wildfire	$0.5 B	$7 B	$4 B	$45 B
Severe Storm	$3 B	$19 B	$13 B	$36 B
Flood	$4 B	$54 B	$4 B	$27 B
Total annual cost	$24 B	$158 B	$91 B	$565 B

The total annual cost in Model 2 is greater than the total annual cost in Model, which is principally driven by the increase in annual costs due to tropical cyclones and severe storms. The average annual cost in Model 2 is 3.8 times larger than that of Model 5 ($91 billion compared to $24 billion). The 99-percentile cost of Model 2 is more than $400 billion more than that of Model 5. This comparison supports the conclusion that the billion-dollar disasters have gotten more frequent and/or more costly since 2000, and the main reason for this increase is due to increasing costs from tropical cyclones and severe storms.

CHAPTER 5. DISCUSSION

There are limited amount of resources and money in the United States to protect against and prepare for natural disasters. The mathematical models are one of the best tools available to analyze and model natural disasters that can help the policymakers determine where the resources and capital should be spent in order to create the biggest effect in reducing the risks from the natural disasters and enhance resilience. Managing risks and resources can save American lives and reduce cost of damage from disasters. The probabilistic models of the cost of the billion-dollar natural disasters are generated in this thesis. These probabilistic models quantified the risks in economic value from billion-dollar disaster. The risk analysis models in this thesis have not only classified the disasters by frequency and the disasters which can result in most severe economic consequences, but also incorporated the inherent uncertainties of the natural disasters. Policymakers can use the information provided by the models to determine the ways to effectively allocate resources to each type of disaster for protection against and preparing for natural disasters based on the probability distribution of the economic costs of the billion-dollar natural disasters. Risk analysis models can be used as a guideline to invest in the future generations of the country and build a robust economy around the disasters.

This thesis helps in assessing the likelihood of costs from seven types of billion-dollar natural disasters. We forecast the economic consequences of billion-dollar natural disasters using Monte Carlo simulation. Five models are designed to evaluate the risk and forecast the costs of billion-dollar disasters. Model 1 and Model 2 use the billion-dollar disaster data. Since some of the increase in the cost of the billion-dollar disasters is likely due to the growth in the GDP, Model 3 and Model 4 incorporate GDP into the model. Model 1 and Model 3 use all the data from 1980 to 2018, while Model 2 and Model 4 use only the most recent data. Model 5 uses the data from

1980 to a year prior to Model 2 as depicted in Table 3 for each type of disaster. The annual frequency and cost for each of the seven different types of disaster are modeled separately. These separate costs of each type of disaster are combined into a single total annual cost. Monte Carlo simulation enables us to incorporate the different uncertainties into a single probabilistic forecast of the annual cost of billion-dollar disasters in the United States.

A large difference in the forecasted costs occurs if all the data is used or only the most recent data is used to forecast the risks of billion-dollar disasters. The average annual cost according to Model 1 for all disasters from 1980-2018 is $52 billion with a median of $30 billion and a standard deviation of $95 billion. The average annual cost for disasters according to Model 2 is $91 billion, with a median of $56 billion and a standard deviation of $120 billion. Due to changes in the frequency and the costs of billion-dollar disasters, the average costs of each type of disaster from Model 2 are almost twice as large as the average costs from Model 1. Model 3 and Model 4 capture the effect of GDP on the cost of each disaster and subsequently on the total cost. Model 3, which has identical data as Model 1 for the costs of disasters, produces an average annual cost of $78 billion, which is 50% higher than the average annual cost from Model 1. One of the reasons for higher costs from Model 3 as compared to Model 1 is drought. Losses from drought were substantially higher during 1980 ($33 billion), 1988 ($44 billion), and 2002 ($13 billion) when compared to GDP in those years. Model 4 has the highest expected annual average cost ($108 billion), median ($62 billion), and the 99th percentile ($681 billion) of all the models. These extreme disasters tend to skew distribution towards the right and overestimate the cost. As can be seen from the Q-Q plots in Figure 6, Model 3 and Model 4 seem to overestimate the annual costs of extreme natural disasters.

The first four models demonstrate that tropical cyclones have the most severe impact on the U.S. economy. Extreme disasters such as Hurricane Katrina, Hurricane Harvey, and Hurricane Maria have each resulted in $93 billion or more in economic costs in the past, which is evident from the models. The annual average cost from tropical cyclones is more than $30 billion according to Model 1 and more than $60 billion according to Model 2 and contributes 60-70% of the annual costs. The cost to the U.S. economy by tropical cyclones is approximately five times more than the second most expensive disaster (severe storms) in both Model 1 and Model 2. Similarly, tropical cyclones also have the greatest average annual cost in Model 3 ($37 billion) and Model 4 ($68 billion). Tropical cyclones also exhibit the largest increase in costs since 2000 when comparing the results between Models 2 and 5.

Even though tropical cyclones incur the highest cost to the economy, the most frequent billion-dollar disaster is a severe storm in the four models. According to Model 1, Model 2, and Model 4, severe storms have the second-highest annual cost from $6-15 billion. Wildfires have the second-largest average annual cost in Model 3 at $13 billion, and the average annual cost of severe storms is $8 billion in Model 3.

Droughts contribute the third largest impact according to Model 1, Model 2, and Model 3, with an average cost of $6, $7, and $11 billion, respectively. Losses from wildfire ($12 billion) are the third-largest contributor to the total average cost according to Model 4. This change in losses for wildfire is also noted in Model 3, which might be because of the fewer data points for wildfire compared to the severe storm that cost higher than the GDP of that period.

The five models seem to have some benefits and drawbacks. Models 1 and 3 use all of the available historical data, which is generally good practice, especially when the size of the dataset is rather limited. However, since the frequency and costs of billion-dollar disasters appear to be increasing, only using the most recent data as Models 2 and 4 do seem reasonable. Incorporating GDP into the model to account for some of the increase in costs might be appropriate. Still, Models 3 and 4 do not seem to fit the data very well and may overestimate these natural disasters' costs. Model 2 seems to provide a good fit to the historical data and account for the rise in frequency and costs due to its ability to incorporate recent disaster cost and frequency changes.

Previous researchers have mentioned the importance of education and experience on disaster preparedness [33], [34]. Educating vulnerable populations about the effect of tropical cyclones (most expensive disaster) and severe storms (high-frequency disaster) can significantly reduce the economic impact and save American lives. A dollar invested by the federal government in disaster mitigation saves six dollars in recovery [35]. The mitigation efforts could be an input in the risk analysis models generated in this thesis so as to quantify, forecast and understand the outcome of mitigation strategies on the total economic costs of disasters. The valuation of economic costs of disasters from the models can be utilized by policymakers to estimate the effectiveness of recovery plans. The ability to mathematically quantify different complex natural disasters can be used by the policymakers to compare different scenarios at different levels of severeness. A rank order system could be generated using appropriate multi-criteria decision making methods with different scenarios to support and determine separate mitigation strategies. A proactive measure and numerical modeling approach, described in this thesis for highly disruptive disasters such as tropical cyclones, severe storms, and drought, can substantially mitigate the adverse effects [34]. Disaster risk reduction (DRR) has been shown to mitigate the economic impacts of natural disasters [36]. Based on the above models, spending 30-50% on tropical cyclones can fast-track the economic recovery.

This thesis uses probabilistic models. The models quantify the distribution of possible losses and the likelihood of their occurrence. The data collected by NCDC shows some limitations. Some natural disaster losses take a longer time to realize to the economy, and it might take months or years before receiving accurate information. The models are also limited to natural disasters contained in the dataset and do not consider the types of disruptive events such as a pandemic or terrorist attack. A future extension of this work could include a model with the number of deaths. Quantitative measures can be refined further by incorporating subject matter expertise through Bayesian analysis. Ultimately, the strength of these models lies in the ability to incorporate complexities and uncertainties of the natural disasters and to help quantify these uncertainties to enhance effective decision making.

These types of models can help policymakers understand the risk of large-scale natural disasters and help them be better prepared and create a more resilient nation. This thesis provides one way of quantifying and understanding risks in the overall efforts towards building risk management strategies. Quantifying and analyzing the costs of these disasters using probabilities can inform policymakers about how much they should spend in order to prepare for and hopefully reduce the frequency and magnitude of these billion-dollar disasters.

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