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Time series analysis and probabilistic model of the financial costs of major disasters in the USA

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Abstract

The number of billion-dollar natural disasters in the USA has increased from 28 in 1980–1989 to 105 in 2010–2018. During these same time periods, the total cost of these natural disasters increased from $172 billion to $755 billion. Generating probabilistic assessments of the cost of these billion-dollar natural disasters can provide insight into the financial risks posed by these disasters while accounting for the uncertainty and variation in these disasters. This article simulates the frequency and cost of billion-dollar disasters and analyses the financial risk of these disasters in the USA. We use a probabilistic approach to quantify and create five models. These models are created by fitting probability distributions to the historical cost of billion-dollar disasters. The model that fits the data best and accounts for the recent increase in the cost and frequency of billion-dollar disasters forecasts that the expected annual cost of these disasters is $91 billion, with about a 1% chance that the annual costs could exceed $500 billion. Simulating the costs and frequency of natural disasters provides an understanding of the risks of different types of disasters in the USA.

Keywords Billion-dollar disasters · Probabilistic risk assessment · Gross Domestic Product · Simulation

1 Introduction

From 1980 to 2018, the USA sustained nearly 250 weather and climate events with a cost of $1 billion or more (adjusted to 2018 U.S. dollars). The total cost of all the billion-dollar natural disasters in these 38 years exceeds $1.7 trillion (National Centers for Environmental Information (NCEI) 2019). The average annual cost from billion-dollar natural disasters 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 USA in 1980–1985, and 72 billion-dollar disasters occurred in 2013–2018. Table 1 shows the number and total cost of billion-dollar disasters in every decade. Seventy-two out of 244 billion-dollar disasters, nearly 30% of the total number of disasters, occurred in 2013–2018, and they account for almost one-third of the total costs. These costs are adjusted for inflation using the 2018 Consumer Price Index. See Kazimi and Mackenzie (2016) for a good review of previous studies that estimate the economic costs of natural disasters. The billion-dollar disasters are categorized into seven types of natural disasters: freeze, tropical cyclone, winter storm, drought, wildfire, severe storm, and flooding.

When a billion-dollar disaster occurs, it frequently garners significant media. Academic research often analyzes emergency preparedness and response for a billion-dollar disaster. A myriad of journal articles on emergency preparedness and disaster resilience exist; however, policymakers often struggle with allocating resources to prepare and respond to disasters in part due to the uncertainty inherent in disaster preparedness (He and Zhuang 2016; Dudley et al. 2019). These billion-dollar disasters frequently appear in journal articles as case studies or illustrative examples to demonstrate how a mathematical model or analysis can help the USA better prepare for and respond to disasters. When researchers and policymakers discuss how the nation and its communities need to be more resilient to natural disasters, these billion-dollar disasters often serve as the type of disaster for which we need to mitigate the risk.

Several factors contribute to the difficulty in preparing for and responding to these large-scale disasters, but one important factor is the uncertainty and variability of these

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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
Total	244	$1702 B	100

disasters. Considerable uncertainty exists in how frequently these disasters occur and the extent of damage that a disaster may cause (Farber 2010; Button 2016). The data suggest that billion-dollar disasters occur more frequently than they did in the past and are more costly. However that does not mean that each succeeding year will necessarily have more billion-dollar disasters or more costly disasters than the previous year. Each of the seven types of natural disasters may follow a different pattern and occur with different frequencies with different costs. For example, the average cost of droughts during 1980–2000 is greater than the average cost of droughts during 2001–2018. The average cost of tropical cyclones during 1980–2000 is less than the average cost of tropical cyclones during 2001–2018. The largest cost from a flood was approximately $40 billion in 1993, and the smallest cost from a flood was $1 billion in 2016 (converted to 2018 U.S. dollars). Considerable annual variability exists in the number of billion-dollar disasters, the specific mix of natural disasters that comprise the billion-dollar disasters in any given year, the cost of each disaster, and the total cost of all billion-dollar disasters in a year. This uncertainty and variability in disaster cost pose a tremendous challenge in precisely modeling these disasters.

One of the principles in risk management is to quantify risk using the likelihood and consequences of undesirable events (Kaplan and Garrick 1981; Kunreuther 2002). A probability distribution of the consequences is perhaps the gold standard of risk assessments (Hubbard 2014). A probabilistic description of the consequences can be used to understand the seriousness of the risk, compare and prioritize among different risks, and ultimately determine what should be done, if anything, to mitigate the risk. Probabilities that describe the uncertainty and numerical estimates of the consequences enable good decision-making for risk. Quantifying the losses from disasters help defines priorities for policymakers on where to allocate resources and how to evaluate the effectiveness of risk mitigation activities. Insurance companies also require reliable disaster estimates for their portfolios. Simulations are a good way to combine data from different sources to quantify the risk and visually present information using charts and histograms.

Despite the importance of probabilistically assessing the consequences, no research to our knowledge has attempted to model the annual costs of these billion-dollar disasters probabilistically. Previous research into billion-dollar disasters either focuses on a single disaster or examines and improves on the methodology to estimate the economic cost of natural disasters. Some researchers have assessed the uncertainty in those estimates and attempted to identify factors contributing to the more frequent and costly natural disasters (Smith and Matthews 2015). Much of the discussion of uncertainty around billion-dollar disasters focus on uncertainty in estimating disaster losses (Romão and Paupério 2016). Data-driven approaches are increasingly informing comprehensive model-based analysis. More work needs to be done in organizing poor, fragmented, and inconsistent available knowledge (Molinari et al. 2014). The previous research has not attempted to assess the uncertainty in the number of billion-dollar disasters, the specific type and cost of each disaster, and the total costs for natural disasters.

Reliable disaster loss accounts are fundamental to establishing loss trends and spatial patterns (Kunreuther and Michel-Kerjan 2007). These are used to measure the success and failure of public health and safety policies. Disaster loss data are also important for defining priorities for funding scientific research fields and for evaluating the contribution and effectiveness of scientific advances for disaster mitigation. Insurance companies also require reliable disaster loss accounts in their portfolios (Sturm and Oh 2010; Kunreuther 1996).

This article is unique because this research probabilistically assesses the annual cost of billion-dollar disasters. The probabilistic assessment is based entirely on the database of billion-dollar disasters and the Gross Domestic Product (GDP) of the USA. Rather than attempting to model the entire set of billion-dollar disasters, each of the seven types of natural disasters is modeled separately. We used one probability distribution for the frequency of a specific type of natural disaster and another probability distribution to describe the costs incurred due to a disaster. After obtaining frequency and cost distributions, Monte Carlo simulation combines these probability distributions into an overall picture of the risk of billion-dollar disasters in the USA. This approach to separately modeling and combining extreme disasters provides a more extensive understanding of the losses in the USA. Simulations aid in identifying different scenarios of what could happen and in drawing better conclusions to make the nation more resilient to natural disasters.

This article is divided into five sections. Section 2 identifies the open questions from the literature review. Section 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 incorporate the U.S. GDP. One model compares the results to validate the best model. Section 4 discusses the outcomes of fitting distributions to the data and the Monte Carlo simulation. The discussion in Sect. 5 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.

2 Literature review

A number of studies have estimated the economic impact of natural disasters. Some of the most common models to estimate economic losses are the Input–Output (I–O) and the Computable General Equilibrium (CGE) models (MacKenzie et al. 2012). These models consider the economy as a collection of industries that interact with each other through intermediate consumption. Models are generated to fit the specific scenarios to measure the reduction in GDP in areas impacted by the disruptions to predict the impacts of disasters across different regions (Oosterhaven and Bouwmeester 2016). Some authors have attempted to isolate parts of the state of California (Rose et al. 2016) and its impact on the rest of the U.S. economy. These economic models identify the direct and indirect losses from disasters (Leontief 1936; Keen et al. 2003; Rose and Liao 2005). Al Kazimi and MacKenzie (2016) review several I–O and CGE studies of past and potential disasters in the USA. The estimates in total economic losses on a national scale from these models can differ by as much as a factor of seven (Koks et al. 2016). These differences are mainly due to assumptions made by the models.

The National Weather Service (NWS), a federal agency within the National Oceanic and Atmospheric Administration (NOAA), provides weather-related products and services to the public. NWS has maintained a historical database of flood damage in the nation since 1870. The accuracy of these flood datasets has been tested and shown to be consistent but not perfect (Downton and Pielke 2005). The errors and uncertainty in data arise while collecting and estimating the economic impact. The variability could be due to a combination of many factors, including incompatibility between different sources, human error, population changes, changes in wealth or economic development of the impacted area, and extreme weather disasters skewing the overall results. In the 1980s, NOAA's National Climatic Data Center (NCDC) started tracking individual U.S. weather and climate events that cost at least $1 billion in overall damages and costs (Lott and Ross 2005). The data collected by NCDC rely on insurance companies and government agencies. Researchers have identified new approaches to quantify the uncertainty in this data source (Smith and Matthews 2015).

Several weather agencies and climate-economic research have mentioned that the cost and frequency of natural disasters are increasing (Coronese et al. 2019). The increase in the frequency and costs of billion-dollar disasters could be due to several factors, including climate change, population increase, and economic activity. Over 80% of the nation's total losses from weather and climate events are caused by billion-dollar disasters (NCEI 2019). The real U.S. GDP was $6.95 trillion in 1980 and $18.93 trillion in 2018 (FRED 2019). U.S. 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 USA has grown faster than the nation's GDP.

The billion-dollar disaster weather data published by NOAA and used in this article likely underestimate losses by 10–15% (Smith and Katz 2013). Due to the complexity of the U.S. economy, the data on losses from natural disasters contain significant amounts of uncertainty (Kron et al. 2012), and the full extent of material losses may not be known until several years after the disaster. The cost of some disasters might be over-estimated. For example, rain from a hurricane might benefit agricultural crops yet damage other industries (Lott and Ross 2005). Due to this uncertainty, Smith and Matthews (2015) attempted to construct a confidence interval around the billion-dollar disasters dataset.

After a natural disaster, government agencies, institutions, and insurance companies publish their estimate of the cost of the disaster. These estimations use various methodologies and different approaches to collect data. 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 (Downton and Pielke 2005). As the area or the period of time is extended, the underestimation and overestimation errors tend to average out. The errors are significantly less for events that cost more than $500 million. Extreme climate events cause damage to crops due to floods (Changnon and Hewings 2001), which can affect the nation's ability to self-sustain during a crisis. The cost and frequency of wildfires and droughts have also increased over recent years (Whitman et al. 2019). The continuous effect of drought stresses trees and wildlife, which increases the risk of forest fires (Littell et al. 2016). Long-term and short-term drought can influence wildfire. We attempt to account for this relationship between drought and wildfires in our models.

Research has tried to estimate the impact of different types of disasters separately (Peterson et al. 2008). Studies have shown that frequency of heavy precipitation events, such as flooding, and the frequency and intensity of tropical cyclones have increased in North America in the past few decades (Climate Change Science Program 2008; Elsner et al. 2008). Some studies have claimed that the increase in the intensity of tropical cyclones from 1982 to 2009 is only marginally statistically significant (Kossin et al. 2013).

There is clear evidence of tropical cyclones getting stronger as a result of global warming from 1979 to 2017 (Emanuel 2020). A probabilistic model by Pall et al. (2011) concludes that the risk of flood occurrence in the United Kingdom substantially increased in 2000 due to anthropogenic greenhouse gas emissions. In 1993, approximately 3.3 million ha of soybean and corn fields were flooded in the American Midwest, causing a 50% decrease in corn yields in Iowa, Minnesota, and Missouri and a 20–30% decrease in three other states (Kundzewicz et al. 2014). Recent studies on past and current changes in precipitation extremes in North America have reported an increasing trend in precipitation over the last half-century (Climate Change Science Program 2008). Choi and Fisher (2003) constructed a regression model between annual flood loss and socioeconomic and climate drivers, with a conclusion that a 1% increase in average annual precipitation leads to an increase in annual national flood loss of around 6.5%. Floods also damage transportation infrastructure.

As the world has also become wealthier during the past decades (Gale 2006), the costs of natural disasters have also increased. This makes it harder to evaluate if the cost of the disasters has increased due to increased economic activity and wealth. Flood losses have greatly increased, mainly driven by the expanding assets at risk (Fothergill and Peek 2004). Not all people are equally impacted by disasters. Low-income populations are more physically and psychologically vulnerable to natural disasters (Pendleton et al. 2013), and robust data are needed to assess the impact of disasters on populations with different socioeconomic statuses. Disasters that destroy productive capital tend to reduce GDP, but disasters that destroy consumable goods (such as a car) tend to have no effect or increase the GDP of the nation (Strulik and Trimborn 2019). Public perception also changes with the amount of accurate information people receive from trusted weather and climate agencies (Lazo et al. 2009). Accurate forecasts benefit society in making a range of valuable decisions for their well-being. Even as the scientific understanding of the economic consequences of these extreme events improves, higher-quality data are required to fully understand their economic costs across years, events, and places (Cutter et al. 2013). As data become more available, mathematical models can be extended to multi-event disaster planning to quantify resilience and improve decision-making (Zobel and Khansa 2014). Simulation effectively combines data from multiple sources and quantifies the results to make better data-driven decisions. Policymakers can use these mathematical models to make effective decisions to mitigate the consequences of natural disasters.

Temperature and CO_2 levels have shown a very high correlation with the increase in billion-dollar disasters that could impact the U.S. healthcare system (Bhola et al. 2023). CO_2 emissions are correlated with health care expenditure and economic growth (Yang et al. 2022). This could pose a significant challenge if multiple disasters or a disaster and a pandemic occur at the same time (Feitelson et al. 2022). The economic shocks from multiple sources could be highly disruptive to American lives. Moreover, natural disasters can have disproportionately larger impacts on older adults' mental health (Zhang et al. 2022). Billion-dollar disasters can have a negative effect on an aging society such as the USA where the average age of the population is increasing.

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 (Parwanto and Oyama 2014). Scientific assessment on extreme natural disasters shows evidence toward increase in intensity and frequency of storms and recommends risk-based approaches to resilience (Vose et al. 2014). However, there is no study using a probabilistic approach for tracking the risk of extreme events using the current data (Pendleton et al. 2013). There is a need for mathematical models, improved data, and probabilistic approaches in response to natural disaster anticipation. Better data-driven models could improve the standard of living and save lives.

3 Method

NOAA annually records and publishes natural disasters whose cost exceeds $1 billion. Figure 1 shows substantial annual variation in the costs of billion-dollar disasters from 1980 to 2018. As seen in Fig. 1, the total cost of all disasters in 2005, 2011, and 2017 was significantly greater than in the other years. This is largely due to a few extreme events. The total cost of $221 billion dollars in 2005 was largely due to Hurricane Katrina. The large cost in 2011 was due to Hurricane Irene. Several droughts, Hurricane Harvey, and Hurricane Maria generated large costs in 2017. We initially attempted to fit a probability distribution to this entire data set, but no distribution fits well with the observed data or provided good forecasts. To solve this problem, we divided the dataset and tested multiple models to capture the trend of

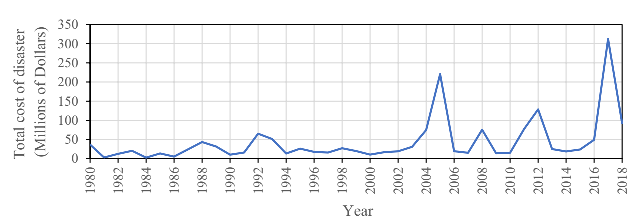


Fig. 1 Total cost of billion-dollar natural disasters from the year 1980 up to the year 2018

billion-dollar disasters. We create these models to incorporate the changes over time and compare the economic costs of billion-dollar disasters. Comparing these models provides insights into the effects of the increase in economic activity and changes in the frequency and costs of natural disasters in the past four decades.

Emergencies and disasters impact the nation and its population, especially if the disasters have a large economic impact. Disaster preparedness is challenging, and allocating resources for billion-dollar disasters is even more difficult due to competing priorities and limited resources (Khan et al. 2018). The current quantitative results seem inadequate in disaster planning to make the most effective strategies and resource allocation (Timbie et al. 2013). 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.

A better approach than fitting a model to all 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.

Table 2 depicts the cost and percentage impact of the billion-dollar disasters from 1980 to 2018. The costs of disasters are unevenly spread for each type of disaster and split into unequal percentages.

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 (e.g., 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 tests to see if the frequencies of any of these disasters are 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 (IID). We use the Akaike information criterion (AIC) (Akaike 1998) and the log likelihood (Barnard et al. 1962) 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.

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

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. The first two models only rely on the costs of billion-dollar natural disasters. Model 3 and Model 4 give insights into the effect of the increase in GDP on the cost of billion-dollar disasters. The last model compares the costs and frequency of disasters in recent years to support the argument that disasters have gotten stronger over time.

Model 1 uses all the historical data from 1980 to 2018 to model the costs of natural disasters. We use all of the data to fit a discrete distribution to the annual frequency for each type of disaster. 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 dollars to the U.S. economy. There are seven different types of disasters, and each disaster has two uncertainties (number of disasters per year and the economic impact for each disaster). A total of fourteen uncertainties are combined to create a picture of the risk of billion-dollar disasters. Some of the frequencies of disasters are also correlated. Monte Carlo simulation, in which the random variables are sampled thousands of times based on the input distributions, is a well-established method to obtain solutions for problems that combine multiple uncertainties (Vose

2008; Law 2015). It is possible to calculate the annual expected cost and the variance of billion-dollar disasters without using simulation, but generating the entire cumulative distribution that combines all seven different types of disasters would be extremely difficult, prone to errors, and may be impossible. A simulation aids in learning what could happen with different scenarios that enables us to derive a more complete picture of the risk of billion-dollar disasters.

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 paragraphs 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.

One explanation for the growth in billion-dollar disasters and the increase in costs from 1980 to 2018 may be the growth of GDP and population in the USA. Accounting for the change in wealth and population in the USA 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 the 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 to 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.

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 a simulated disaster in a trial is negative, we generate another cost for 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 Sect. 4.

4 Results

4.1 Fitting distributions

This article analyzes, fits distributions, and simulates all the billion-dollar natural disasters in the USA from 1980 to 2018. When all the data are 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

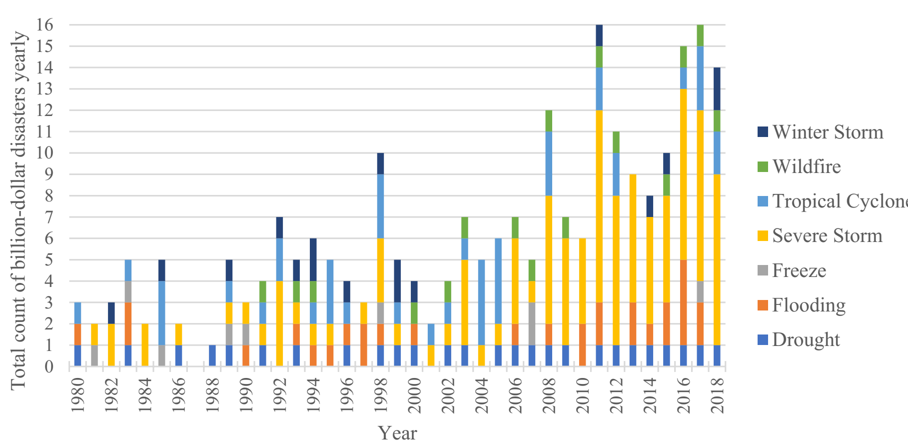


Fig. 2 Frequency of each type of billion-dollar natural disaster from 1980 to 2018 (NCEI 2019)

Table 3 Distributions of the annual frequency

Disaster type	Type of distribution	Model 1 and 3 parameter	Year model 2 and 4 begins	Model 2 and 4 parameter
Freeze	Poisson	$\lambda = 0.2\,3$	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	$\lambda = 1.3$

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. All 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 Fig. 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 all of the models.

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 to 2018. The SHASH distribution's

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

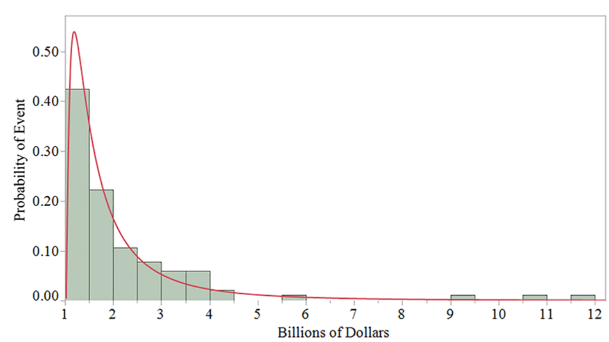


Fig. 3 Fitted Johnson distribution to severe storm dollar value during the period 1980–2018

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

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

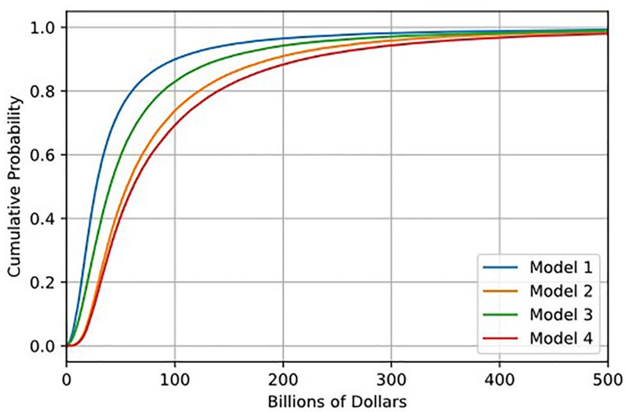


Fig. 4 Combined cumulative probabilities generated by the four models

disasters as possible, and we select the Johnson distribution to model the cost of each type of disaster except for the winter storm in Model 2. The AIC and log-likelihood values for the Johnson distribution remain within 10 of the best distribution for each type of disaster in all of the models, except for winter storm and drought. For winter storm, the AIC value of the Weibull distribution is 79.5, while the AIC value of the 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 types.

4.2 Simulating economic costs

As mentioned, 100,000 simulations are generated for each model. Figure 4 shows the cumulative probability of the annual costs for each model, given the disaster is a billion-dollar disaster. According to Model 1, which is based on all of the data from 1980 to 2018, the expected cost of all billion-dollar 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 \$150 billion. The vast majority of the simulations result in costs of less than \$80 billion. However, some simulations result in costs of \$200, \$300, or even \$400 billion. As seen from Fig. 4, the likelihood of costs exceeding \$300 billion is very small. Model 1 suggests that the USA should plan for \$20 to \$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 of billion-dollar disasters, 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 of 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 the 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 USA should plan for about \$40 to \$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 the 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 2018. 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 Fig. 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 from the billion-dollar disasters will exceed \$100 billion and a 10% chance the annual cost will exceed \$200 billion.

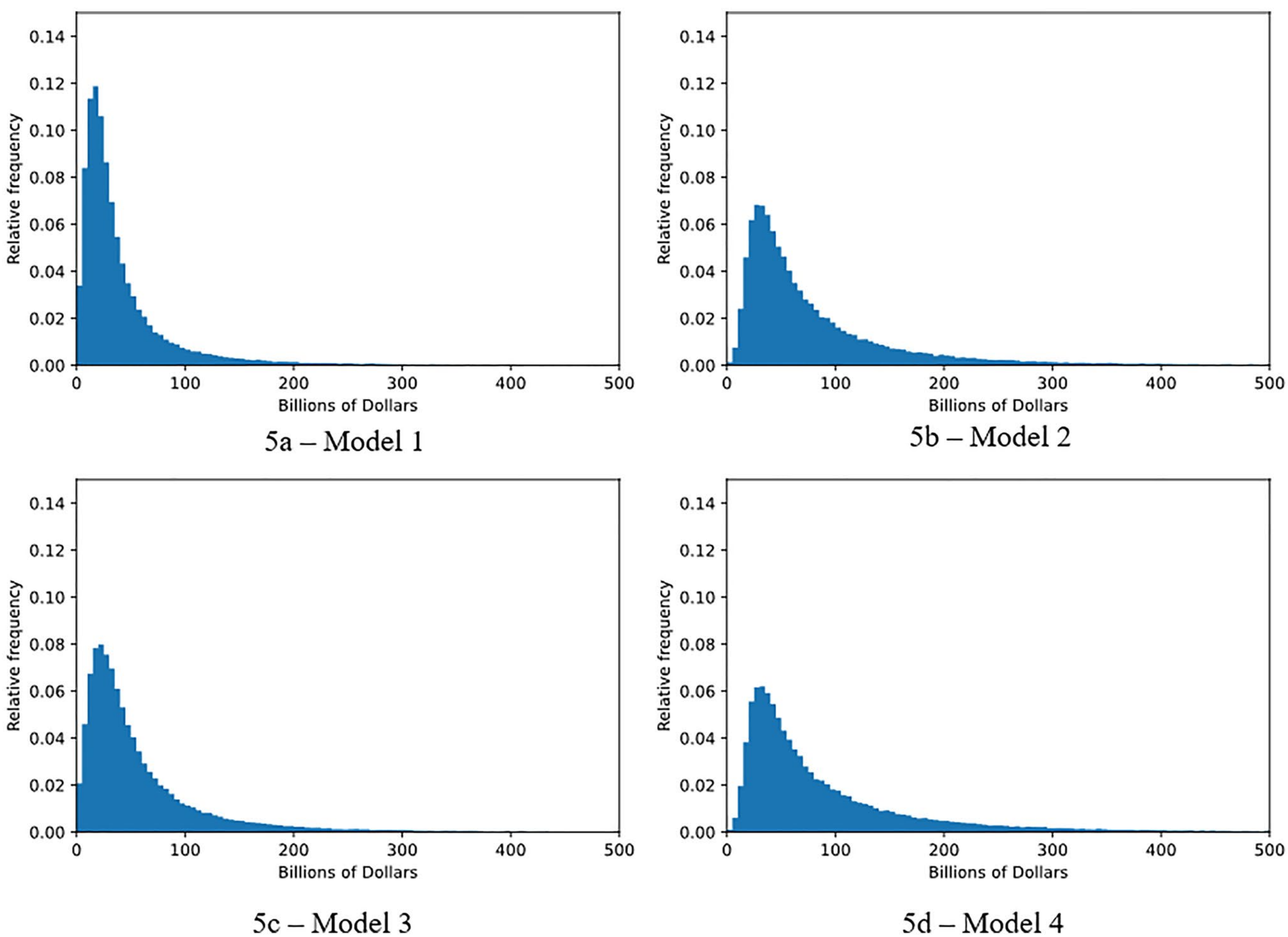
Table 6 presents the simulated annual costs for each of the seven types of billion-dollar disasters. The 99th percentile is depicted in order to show the very extreme or 1-in-100-year scenario. Since none of the disasters are perfectly correlated to each other, as shown in Table 3, the sum of the 99th percentile of each type of disaster will not be equal to the 99th percentile of the total cost. The 99th percentile of the total costs from the billion-dollar disasters 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

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

four models. Model 2 shows a 90% increase in the costs of tropical cyclones compared to that of Model 1, which illustrates 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 depict that the cost and frequency of severe storms are also growing. The winter storm is the least expensive billion-dollar disaster among all the seven types of weather and climate disasters. The average cost of winter storms is always less than 3% of the total average cost for the four models.

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



5a – Model 1

5b – Model 2

5c – Model 3

5d – Model 4

Fig. 5 Relative frequency histogram of annual costs of disasters by each of the model models is highly skewed to the right and unimodal. The major proportion of the costs are less than $100 billion for the four models. Models 3 and 4 show significant right-hand skewness with relatively fat tails and a higher number of years with costs more than $100 billion. Incorporating GDP into the models appears to result in larger forecasts of the costs of disasters.

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. Figure 6a and c shows the models which use all the data from 1980–2018, whereas Fig. 6b and d uses the yearly data from 2000 to 2018. Figure 6b–d demonstrate that their corresponding models may overestimate the actual costs since the plotted points are to the right of the 45° line. In Fig. 6a, the plotted points lay much more consistently along the 45° 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.

4.3 Comparison between 1980–2000 and 2000–2018

The statistical forecast 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. To understand the change in the trend of cost of billion-dollar disasters from the year 1980 to 2000 and more recent years, 2000 to 2018, we create another model. We compare the results from Model 2 with a new model (Model 5). 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. Model 5 uses the costs and frequency of each type of disaster from 1980 to the year prior to the year used in Model 2, as shown in Table 3.

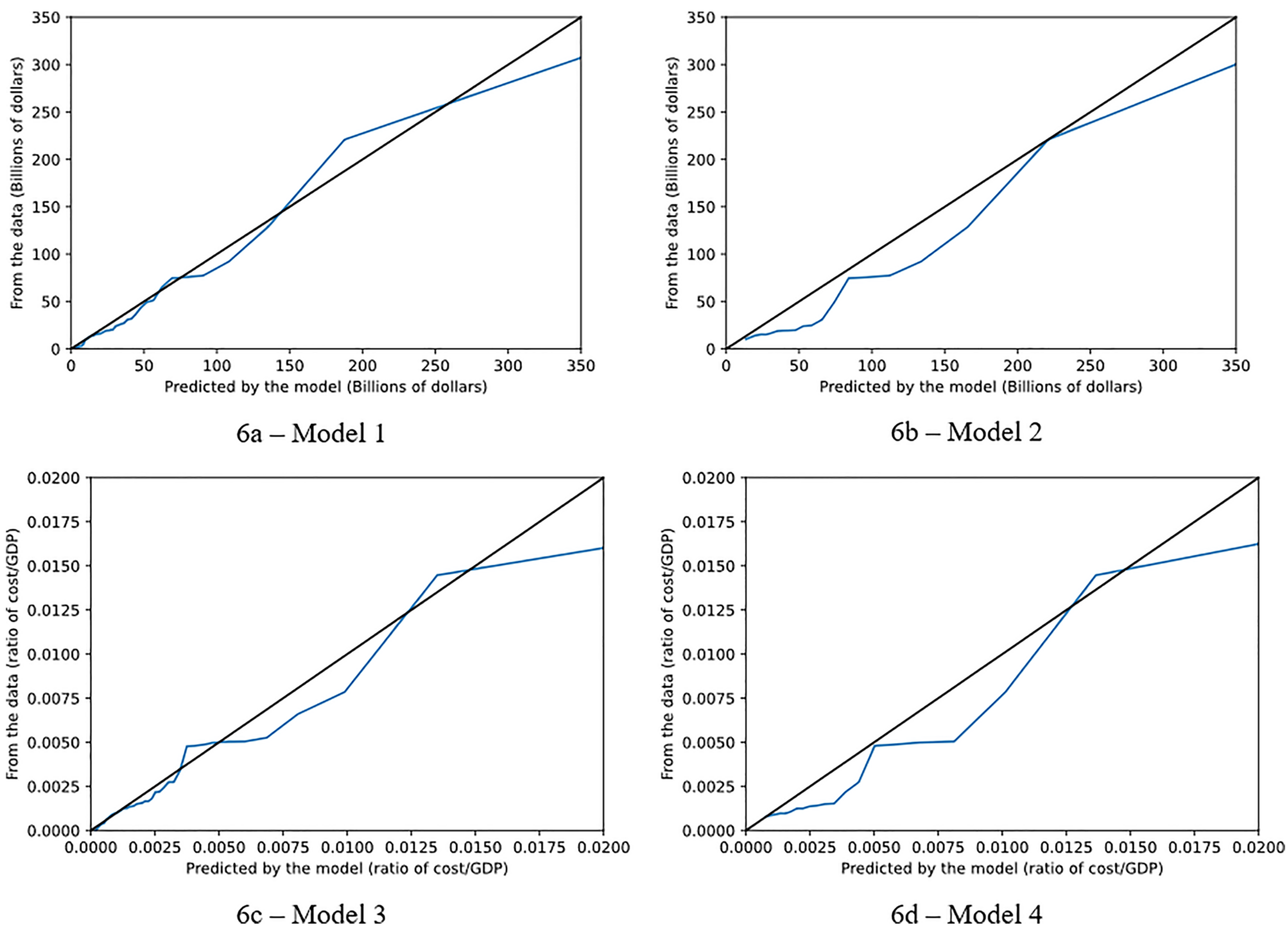


Fig. 6 *Q*–*Q* probability plot of the annual cost of disaster for each of the models

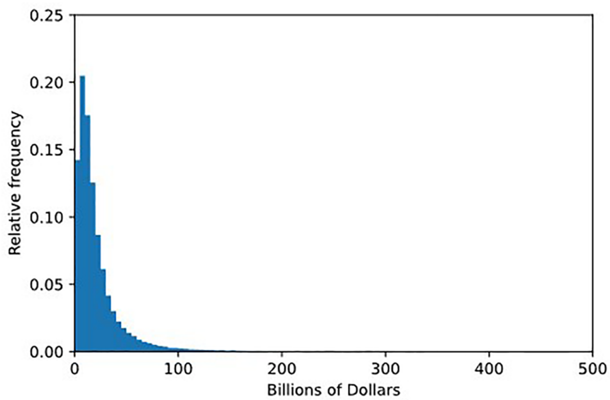


Fig. 7 Relative frequency histogram of annual costs of disasters from 1980 to 2000 of Model 5

Table 7 Cost generated in billions of dollars for each type of disaster 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

We follow all the steps as in Model 2 to fit the distribution to frequency and cost for each type of disaster. 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 in Model 2, and Model 5 contains many more disasters, less than $30 billion compared to Model 2.

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 costs of tropical cyclone, wildfire, and severe storm 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 in 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 cyclone, wildfire, and severe storm have greatly increased in frequency and/or severity in the 2000s.

The total annual cost in Model 2 is greater than the total annual cost in Model 5, which is principally driven by the increase in annual costs due to tropical cyclones and severe storms. The average annual cost of 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. It implies that the extreme disasters might get more extreme in the following recent years. This comparison supports the conclusion that billion-dollar disasters have gotten more frequent and more costly since 2000, and the main reason for this increase is due to increasing costs from tropical cyclones and severe storms. It is also supported by other research done in 2020 using satellite imagery that the intensity of tropical cyclones has increased over time due to greenhouse gas-induced climate change (Emanuel 2020). This research fills the gap in cost assessment by probabilistically estimating the costs of these billion-dollar disasters individually and combined. Comparing Model 2 and Model 5 also provides the time period after which the economic cost of disasters has significantly increased.

5 Discussion and conclusion

There are a limited amount of resources and money in the USA to protect against and prepare for natural disasters. Mathematical models are one of the best tools available to analyze natural disasters to help policymakers determine where resources should be allocated in order to create the biggest effect in reducing the risks from natural disasters and enhancing resilience. Managing risks and resources can save American lives and reduce the cost of damage from disasters. Probabilistic models of the cost of billion-dollar natural disasters are generated in this article. The risk analysis models in this article analyzed the disasters according to their frequency and economic costs while considering the inherent uncertainties in natural disasters. Policymakers can use information based on the probability distribution of the economic costs of billion-dollar natural disasters to determine how to effectively allocate resources for each type of disaster for protection against and preparation for natural disasters. Risk analysis models can be used as a guideline to invest in the country's future generations and build a robust economy around disasters.

This article assesses 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, and the damages from the billion-dollar natural disasters have been converted to 2018 US dollar. Model 1 and Model 2 use 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. Model 2 and Model 5 are then compared to draw some conclusions. 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 USA.

A large difference in the forecasted costs occurs if all the data are used or only the most recent data are used to forecast the risks of billion-dollar disasters. According to Model 1, the average annual cost for all disasters for 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 99th percentile (\$681 billion) of all the models. These extreme disasters tend to skew distribution toward the right and overestimate the cost. As can be seen from the *Q*–*Q* plots in Fig. 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. 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 storm) 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 of \$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 wildfires (\$12 billion) are the third-largest contributor to the total average cost according to Model 4.

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 the costs of these natural disasters. 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 costs and frequency changes.

Previous research has mentioned the importance of education and experience in disaster preparedness (Hoffmann and Muttarak 2017; Torani et al. 2019). Educating vulnerable populations about the effect of tropical cyclones (the most expensive disasters) and severe storms (high-frequency disasters) could reduce the economic impact and save American lives. A dollar invested by the federal government in disaster mitigation saves six dollars in recovery (Gall and Friedland 2020). Proactive measures and numerical models can mitigate the adverse effects of highly disruptive disasters, such as tropical cyclones, severe storms, and drought (Hoffmann and Muttarak 2017). Disaster risk reduction has been shown to mitigate the economic impacts of natural disasters (Shreve and Kelman 2014). Mitigation efforts could be input into the probabilistic models in order to quantify, forecast, and understand the impact of mitigation strategies on the total economic costs of disasters. The ability to mathematically quantify different complex natural disasters can be used by policymakers to compare different scenarios at different levels of severity.

The data collected by NCDC show some limitations. Some natural disaster losses take a long time for the economic impacts to be fully realized. The models are also limited to natural disasters contained in the dataset and do not consider other types of disruptive events, such as a pandemic or terrorist attacks. Disasters that cost less than $1 billion are excluded from this analysis. Billion-dollar disasters account for 80% of the damage from all recorded weather and climate events in the USA (NCEI 2019), so the analysis in this article accounts for the vast majority of costs of natural disasters. A disaster that costs slightly less than $1 billion may eventually be included in the database if inflation increases the cost to $1 billion in current dollars. To our knowledge, no database exists that includes weather and climate events that cost less than $1 billion. Future research could seek to construct such a database and include sub-billion-dollar disasters in this analysis to present a fuller picture of the costs of natural disasters in the USA.

A future extension of this work could also 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 the complexities and uncertainties of 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 article provides one way of quantifying and understanding risks in the overall efforts toward building risk management strategies. Quantifying and analyzing the costs of these disasters using probabilities can inform policymakers about how much resources and budget should be allocated in order to prepare for and hopefully reduce the frequency and magnitude of these billion-dollar disasters.

Author contributions C.S. collected the data, coded the models to analyze the data, and prepared figures and tables. C.M. conceived the idea and helped to interpret the results. Both authors contributed to the writing of the paper.

Declarations

Competing interests The authors declare no competing interests.

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