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Time trends in losses from major tornadoes in the United States

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ABSTRACT

Damage from tornadoes imposes substantial costs on society. This study provides an analysis of time trends in the severity of losses from tornadoes in the United States for the period 1954–2018. Based on information provided by the Storm Prediction Centre (SPC) of the U.S. National Weather Service, we create a dataset of normalized losses from tornadoes spanning 65 years. We then analyse patterns and trends in the total annual losses from tornadoes as well as distributional properties of the damage from individual tornadoes. Our approach allows us to combine observations from the period 1954–1996, when losses from tornadoes were typically reported in a range (e.g. $500,000–$5,000,000) with observations from 1997 onwards when an actual estimate of the damage for an event is provided. Our findings suggest an overall national significant decline in normalized losses from tornado events. At the country level, both the severity of damage from individual events and the total annual losses from tornadoes are seen to have reduced over time. We also find spatial variations in time trends for the damage from tornadoes: while for most U.S. states the declining trend in severity is confirmed, an increasing trend of total annual losses from tornadoes is observed for Alabama.

1. Introduction

Tornadoes have been a significant source of natural hazard in the United States and around the world, with single events having the potential to cause more than $3 billion in damage (Simmons et al., 2013) or resulting in more than 150 deaths. There is a significant concern that the frequency and severity of tornadoes or extreme wind may further increase due to climatic change (Knutson et al., 2010; Diffenbaugh et al., 2013; Jung and Schindler, 2021; Outten and Sobolowski, 2021), making appropriate risk assessment for tornadoes even more important for policy makers, the insurance industry and home owners (Brooks et al., 2014; Tippett et al., 2016). The acceleration of weather extremes also induces the need for adaptation to mitigate potential damages from natural hazards (Travis, 2014; Boero et al., 2015; Sillmann et al., 2017). Given the potentially substantial losses from extreme weather events, risk quantification also plays a critical role in climate adaptation to reduce the vulnerability of housing and important infrastructure to catastrophic events (Ross and Carter, 2011). Natural hazard risk assessment is also useful for various organizations to enhance their operation efficiency in presence of extreme weather (Zhang, 2021) and for people who need to assess their need to purchase insurance (Mendes-Da-Silva et al., 2021).

The quantification of economic damages from climate change and climate impacted hazards has been examined in a large number of studies. For recent overviews on quantifying the economic risk of climate change, see, e.g., Hoeppe (2016), Diaz and Moore (2017), Auffhammer (2018), while Botzen et al. (2019) provide a review of models and empirical studies on the economic impacts of natural disasters. Some authors have also focussed more specifically on modelling frequency and severity distributions for natural hazards. Esteves (2013) examine the effect of different probability distributions on modelling extreme events and propose an index for model uncertainty that can be used in designing protection structures. Keighley et al. (2018) use expert opinions to estimate distributional parameters and further quantify costs associated with catastrophic risks from bushfires. More recently, Pitt et al. (2020) investigate generalized additive models for location, scale and shape to estimate conditional probability distributions and economic losses related to catastrophic events.

Despite the importance and direct relevance of tornado research, reliable quantification of financial risks from tornado events as well as estimation of trends in the severity of losses from tornadoes presents a significant challenge. To date, the Severe Weather Database provided by the Storm Prediction Centre (SPC) is the main data source for historical information on tornadoes in the United States, but a significant portion of tornado losses are reported in a grouped data format, making estimation of the tornado loss distribution especially difficult (Elsner et al., 2013; Tippett et al., 2015). As observed by Tippett et al. (2015), databases outside the U.S. also exist but typically

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have insufficient length or quality for a thorough risk analysis. Predicting tornado occurrence based solely on simulation models is difficult, since theoretical arguments and climate model experiments generate conflicting predictions about the impact of environmental conditions on natural disasters (Diffenbaugh et al., 2013). Prediction methods that make the most use of the available data are therefore important. In this paper, we demonstrate a modelling approach that illustrates the importance of normalizing loss data, i.e. adjusting loss data from a sample period that spans several decades of growth in population, wealth and infrastructure, therefore taking into account the substantially increased loss exposure. The applied approach also allows us to appropriately deal with grouped data for the estimation of tornado loss distributions. The method that we propose for combining grouped data with individual data can also be used in other areas such as storm surge risk where adequate data are lacking (Wang et al., 2021).

The quantification of tornado risk has attracted a great number of studies. Brooks and Doswell (2001) is an early study that analyses normalized tornado losses for the U.S. over the period 1890–1995. This study focuses on extreme tornado events for which at least 50 people are killed or real losses exceed $50 million. The resulted dataset accounts for 50% of tornado losses in the SPC database and for these data, no evidence of trend in tornado real losses is found. A similar study by Boruff et al. (2003) examines the temporal variability and spatial distribution of tornado hazards in the U.S. over the period 1950–2000. It is found that the frequency of significant tornadoes (those that cause death and positive damage) has increased from the 1950s to the 1970s and then decreased in the 1980s and 1990s. A similar trend is found for the mean losses per year. The authors attribute the decrease in tornado deaths and injuries over the last 50 years in their data sample to the improved warning technology such as WSR-88D Doppler radar network, increased warning lead times, and improved public compliance with warnings. A shortcoming of these studies is that by focusing solely on extreme tornado events, the results are not as useful to risk mitigation. Recent mitigation studies suggest that risk mitigation is more feasible and economic for less extreme tornadoes (Sutter et al., 2009; Simmons et al., 2015; Ripberger et al., 2018).

Exposure to the tornado damage can increase over time due to population change (e.g., expanding bull's eye effect) and economic growth (Ashley et al., 2014; Ashley and Strader, 2016; Strader and Ashley, 2015; Strader et al., 2017; Simmons et al., 2013). Meaningful statistical inference requires the use of normalization methods that transform losses so that they have the same exposure. A recent study by Simmons et al. (2013) examine the use of various normalization methods for U.S. tornado damage based on the SPC database. They find that different normalization methods lead to quite different results, but normalized tornado losses generally experience a downward trend. Ryan (2018) conducts a similar exercise for tornado losses in Florida and finds that the frequency of tornadoes has actually decreased since 2002, but the lengths of tornado paths has increased.

Simmons and Sutter (2013) further analyse property damage caused by tornadoes recorded in the SPC database. They find a slight decrease of $3 million (in 2007 USD) per year, but the trend is not statistically significant. The authors also provide rankings of states according to the proportions of records with positive damages, which may be useful for the identification of states that have high tornado risk and more complete data.[1] More recently, Diaz and Joseph (2019) apply a zero-inflated modelling approach in combination with artificial neural networks to predict tornado-induced property damages in the U.S. In a first step, the authors develop a neural network that predicts whether a tornado is likely to cause property damage, and then conditional on the outcome of the first step, a second neural network is applied to predict the magnitude of the damage. The chosen approach allows for detailed spatial predictions of tornado-induced property damages that are presented in the form of maps, e.g. for Kansas, Alabama, Illinois, Oklahoma, and Florida. Obtained simulation results suggest an increased amount of high probabilities of damage from tornadoes for the American south.

Total losses from tornadoes depend on not only the severities of each tornado event but also on how frequent these events occur. Several studies have used the SPC database to investigate how the frequency of tornadoes vary over time. Tippett (2014) examine the frequency of tornadoes in different scales and finds that the annual numbers of F0+ (i.e. scales F0 and higher), F1+ and F2+ tornadoes as well as the tornado environment index that is constructed based on convective precipitation and storm relative helicity are all non-stationary. They find an upward trend in the F0+ (i.e. scales F0 and higher) time series, no trend in the F1+ and a downward trend in the F2+ time series. A similar study by Brooks et al. (2014) examines the variability of annual frequency for F1+ tornadoes over the period 1954–2013. It is found that there is no long term trend in the mean tornado frequency but the total number of tornado days in a year decreases over time, while the number of days with 30 and more tornadoes actually trends up.

In a more recent study, Guo et al. (2016) use the approach by Brooks et al. (2014) and examine the trend in the volatility of tornado frequency at the state level. They find that only one third of the states, mostly from the Great Plains and Southeast regions, have significantly increasing trend, while the remaining states have decreasing or near zero trends in tornado temporal variability. The authors suggest that the increased variability in the Great Plains and Southeast regions might be due to the changes in the environmental conditions required to produce supercells or the conditions for landfalling tropical cyclones or quasi-linear convective systems. In a related study, Edwards et al. (2013) observe that the total land-path areas of tornadoes in the United States covers only 10^3 km^2 per year or 0.01% of the nation's conterminous land area. The idea that tornadoes are more region specific is discussed in more detail in a review study by Moore and DeBoer (2019). The authors provide evidence that suggest tornado frequency and intensity increases for some regions, while for others, they decrease. In addition, in the places where tornadoes often occur, the direction of tornado paths have also changed.

The uncertainty about future tornadoes is further illuminated in the study by Diffenbaugh et al. (2013) who examine the impact of global warming on the frequency and severity of thunderstorms and tornadoes. They suggest that any prediction about future changes in these extreme events is highly uncertain due to the lack of a reliable, independent, long-term record of thunderstorms and in particular, tornadoes. It is difficult to provide reliable predictions based on theories only since predictions from theoretical arguments and climate model experiments about the impact of environmental conditions on natural disasters are sometimes conflicting. Based on the Coupled Model Intercomparison Project, Phase 5 (CMIP5) global climate model ensemble, Diffenbaugh et al. (2013) find an increase in the number of days supportive of the spectrum of convective hazards, with the suggestion of a possible increase in the number of days supportive of tornadic storms.[2]

In summary, the SPC database remains an important data source for the study of tornadoes, despite its various discrepancies. The database has been used to improve our understanding of the statistical properties of tornadoes and facilitate risk management for these events in the future. This brief review of the existing research shows that a trend that is found at the national level may not hold at a more granular

[1] For example, Georgia is ranked 4th in total damage and has only 6.3% of records with zero loss events; Indiana is ranked 2nd in total damage and has 20% of records with zero loss events; Ohio is ranked 7th in total damage and has 8% of zero loss events.

[2] The authors define a severe thunderstorm day based on the combination of the convective available potential energy (CAPE), the vertical wind shear (a 6 km layer) and a tornado based on the combination of the CAPE and the existence of strong shear within the lowest atmospheric levels (1 km shear).

scale. This suggests that tornado studies at the state or regional level are particularly important. The review also suggests that this paper is the first that attempts to use grouped data together with individual loss data in the SPC dataset. It is also the first to investigate the dynamics of normalized loss distributions in the U.S.

Our results suggest that loss normalization plays an important role in estimating and predicting tornado loss distributions. Without normalization, losses generally increase over time due to increased loss exposure and inflation rather than more intense tornadoes. We also find a downward trend in the expected normalized losses for the U.S. and for Alabama, but a non-linear relationship for Texas. These results corroborate the findings by Boruff et al. (2003) who find the declining trend in tornado deaths and injuries and are consistent with the findings by Moore and DeBoer (2019) that tornado losses can have different trends in different states. This is also consistent with the findings by Liang et al. (2020) who suggest that hurricane and storm surge risk can change significantly from one area to the next. Different from previous studies, we examine the dynamics of both the mean and the volatility for the log of tornado losses and find that both of these parameters have decreased in recent decades, leading to the decrease in expected tornado losses. These results also suggest that tornado losses have trended downwards in their average value and also in their variation. In addition, we examine high quantiles of the estimated loss distribution and find that the distribution has become less skewed and heavy-tailed over time.

2. Data and preliminary analysis

2.1. The data

Our research uses a tornado event archive maintained by the US government's SPC. The SPC is part of the National Centers for Environmental Prediction (NCEP) that operates under the National Weather Service (NWS). The NWS is part of the National Oceanic and Atmospheric Administration (NOAA) of the United States Department of Commerce. The dataset has been applied in many studies and has often been referred to as the 'SPC dataset' or 'SPC data', see, e.g., Simmons et al. (2013), Cusack (2014), Guo et al. (2016), Fan and Pang (2019), Moore and DeBoer (2019), just to name a few. According to Gall et al. (2009), the initial data collection process of NWS could be a source of systemic biases, involving the computation of losses and the source of the information. Furthermore, the data collection procedure was not entirely consistent, as NWS shifted from reporting grouped loss data to reporting the actual dollar amount of the loss after 1995 (Gall et al., 2009). Despite changes in the collection process for the SPC dataset over the last 70 years,[3] it is worth highlighting that the dataset is most likely the best source of information on losses from tornadoes available and generally considered as being reliable. As pointed out by Simmons et al. (2013), the SPC dataset has been recorded by a single government agency using a relatively consistent approach to damage data collection. Therefore, the dataset is suitable for the application of a normalization approach and statistical techniques in the context of uncertainties in damage estimates.

As natural hazard loss databases, including the SPC dataset, may have data inhomogeneity, see e.g., Gall et al. (2009), suitable treatments need to be taken when using these databases. The most important bias is the *temporal bias* where losses across time are not directly comparable due to changes in loss exposure. We overcome this bias by using the normalization method described in Section 2.2. In addition, the improvements in radar technology also affect the number of tornado events reported in the database. As discussed by Agee and Childs (2014), the implementation of the Weather Surveillance Radar-1988 Doppler (WSR-88D) network in the early 1990s allows for the possibility of detecting mesocyclones that may produce weak tornadoes. This leads to an increase in the number and variability of F0/EF0 tornadoes. To overcome this reporting bias, we follow Tippett (2014) and exclude F0/EF0 tornadoes from our analysis.

Another important *temporal bias* in the SPC dataset relates to the reporting methods used before and after 1995. Before 1995, the group to which a loss belongs, rather than its actual amount, is reported while after 1995, the actual amounts of losses are reported. Generally this type of grouped data can cause a bias in the statistical estimation. Thus, neither a midpoint (mid) or maximum (max) value approach for using grouped data is appropriate to estimate the losses in an accurate manner. However, the innovative approach proposed in this study (Khemka et al., 2023) is designed to exactly deal with this type of problem.

The SPC dataset also has the *threshold bias*. According to the description from SPC, prior to 1996, a zero entry indicates an unknown amount. However, after 1996, entry of zero means unknown amount or rounded amount. Based on the data, we find that 38.4% of our loss data are recorded as zero. To avoid this bias, we truncate our data at $1000 to exclude those unknown or negligible amounts. Gall et al. (2009) also discuss the issue of a potential *accounting bias*, where monetary and direct losses reported in loss databases are biased estimates of the total losses caused by an event. We therefore emphasize that our study is focused on estimating the distribution of quantified monetary losses caused by tornadoes, rather than also including indirect losses. While this approach might have its limitations, it would be far more difficult – if not impossible – to also include estimates of indirect losses into our framework. We argue that although our findings are limited to monetary losses, they are still of significant interest to homeowners, insurance companies as well as government.

Tornado records contain information on the time and location[4] of the tornadoes, and the Fujita (F) or Enhanced-Fujita Scale (EF0+) scale that rates tornadoes based on their maximum damage. The dataset also contains the estimated amount of property loss and crop loss with losses prior to 1996 reported in nine categories.[5] In addition, from 1996 to 2015, loss amounts are rounded and recorded in million dollars, and since 2016, loss amounts are rounded and recorded in actual dollar amounts. After excluding F0 tornadoes and those with zero loss records, there are 28,903 tornadoes remaining in our dataset. Most of these tornadoes (95.91%) occur entirely in one state, and only 1153 and 28 tornadoes pass through two and three states, respectively. The results from Fig. 1 suggest that while there is no trend in the overall annual frequency of tornadoes, the number of more severe tornadoes has actually decreased.

As mentioned above, the SPC dataset also allows for a classification of tornadoes based on generated losses into nine categories. Fig. 2 illustrates that for most loss categories, the number of loss events seems to be increasing. We find that except for Category 2 and 3, the frequency of tornadoes in each category indicated an upward trend. In particular, we find a clear rise in the number of tornadoes with severe losses, i.e. Category 5, 6 7, and 8, for the considered time period from 1950 to 2018. It is noteworthy that at first glance these results seem to contradict the observation of a decreasing frequency of tornadoes with high intensity in the first place. However, as pointed out by Simmons et al. (2013) simply considering reported loss figures

[3] Interested readers can refer to Simmons et al. (2013) for additional details on the collection process and reliability of the SPC dataset.

[4] This includes the initiation point, the endpoint (longitude and latitude), the date and time of occurrence, the length and width of the damage path

[5] More specifically, 0 or blank indicates unknown loss; 1 means less than $\$50$, 2 means $\$50$–$\$500$, 3 means $\$500$–$\$5000$, 4 means $\$5000$–$\$50,000$, …, 8 means $\$50,000,000$–$\$500,000,000$, and 9 means more than $\$5,000,000,000$

[6] For some tornadoes with unknown F-scale, a modified F-scale based on property loss and path length is provided. In this paper, we do not consider these modified F-scale. Details about modified F-scales are available at https://www.spc.noaa.gov/wcm/OneTor_F-scale-modifications.pdf.

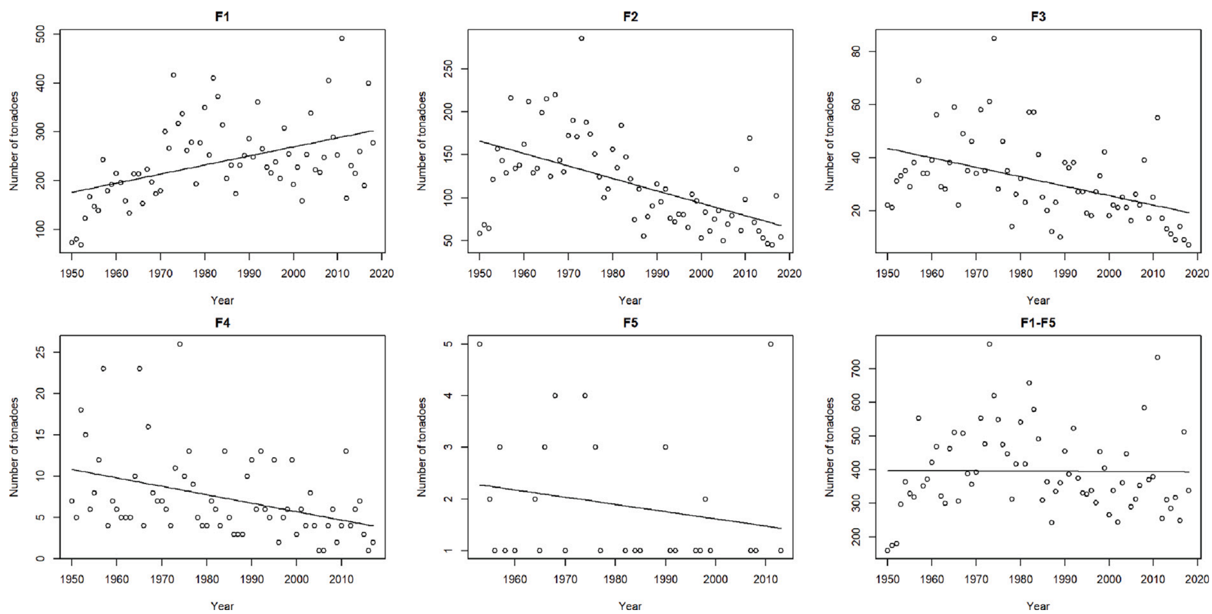

Fig. 1. Number of tornadoes per year for different F-scale categories over the sample period 1954–2018. Tornadoes that cover more than one state are counted only once. Tornadoes with F-scale F0 or unknown F-scale are excluded.[6]Fig. 1 depicts the evolution of tornado frequency over time for each F-scale and for all the considered F-scales (F1–F5). The graphs illustrate that the frequency of tornadoes with a rating of F1 on the F-scale has been increasing throughout our sample period, while the frequency of tornadoes with intensity ratings of F2, F3, F4, and F5 has been decreasing.

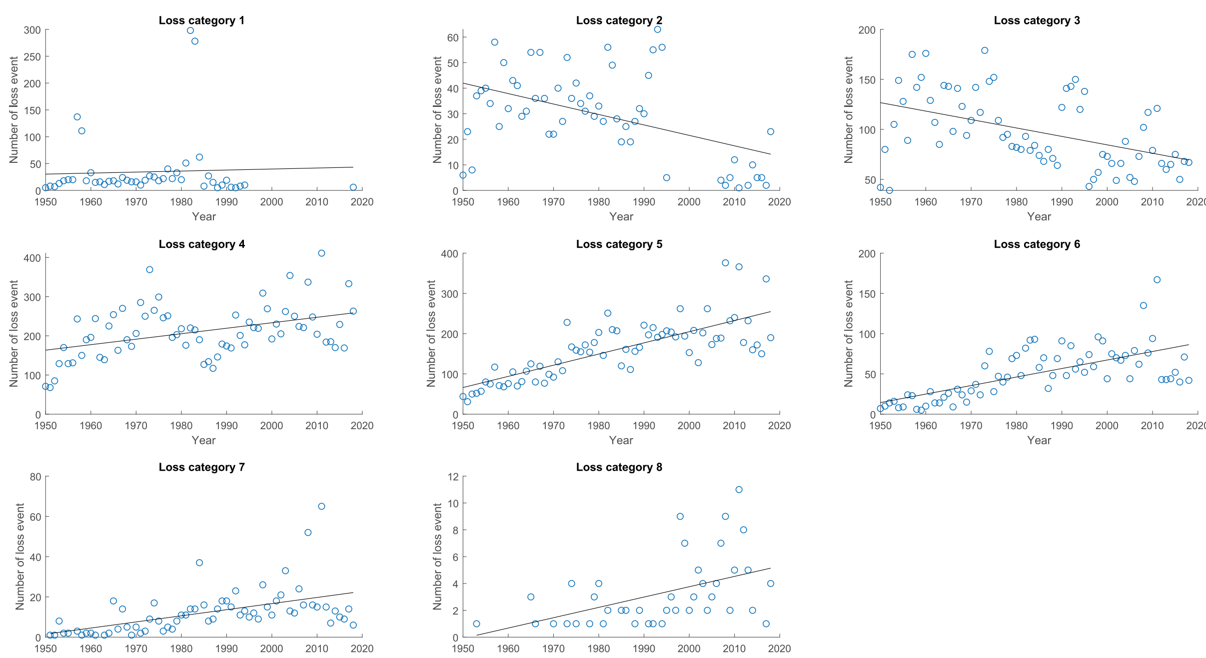

Fig. 2. Number of tornadoes per year across loss categories 1: less than \$50, 2: \$50–\$500, 3: \$500–\$5000, 4: \$5000–\$50, 000, . . . , 8: \$50, 000, 000–\$500, 000, 000. Tornadoes that cover more than one state are counted only once.

without normalizing the data does not allow for a rigorous analysis of trends in the loss and magnitude of tornadoes in a historical context. Given the substantial impact of inflation on reported losses over a 65 year time horizon as well as significant changes in wealth per capita and population, normalizing the reported losses is paramount for an appropriate analysis of the severity of tornadoes through time. Thus, in the following we discuss the implementation of a normalization approach that allows us to compare individual loss events.

2.2. *Proportional normalization for damage data*

Independent of physical changes in the frequency or severity of tornadoes, losses may grow over time simply due to economic or population growth in a region, or because the wealth or property values in the studied region have increased over time (McAneney et al., 2009; Simmons et al., 2013; Strader et al., 2017; Diaz and Joseph, 2019). A related concept that plays a major role in the exposure growth is

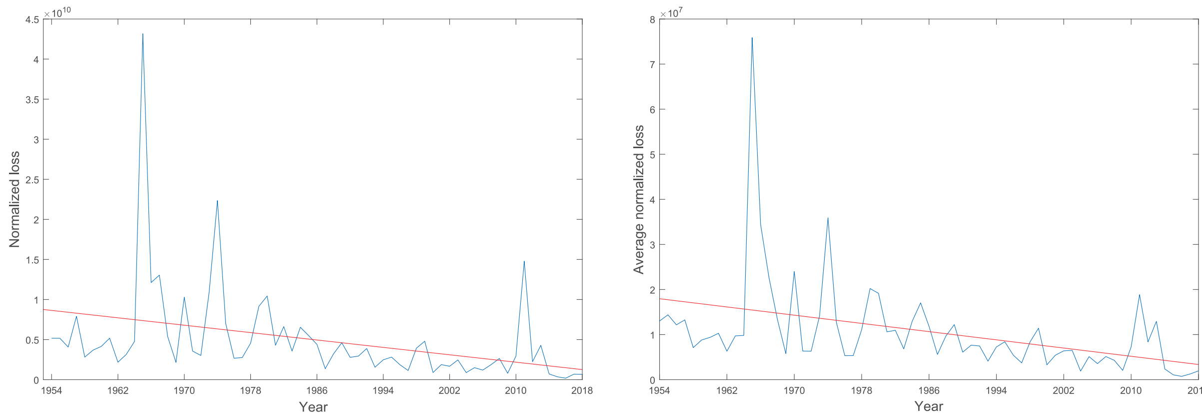

Fig. 3. Annual normalized losses and fitted regression line for normalized losses at the national level for 1954–2018. Results are illustrated for total annual losses (left panel) and average annual losses (right panel).

Table 1
Descriptive statistics for normalized tornado loss events for 1954, 1960, 1970, 1980, 1990, 2000, 2010 and 2018.

Year	Normalization index	Number of events	Mean (in millions)	Median (in millions)	95th percentile (in millions)	Standard deviation (in millions)	Skewness	Kurtosis
1954	53.19	398	13.01	1.46	14.63	105.21	13.28	181.34
1960	38.60	443	9.38	1.06	10.61	72.68	13.83	198.34
1970	19.70	429	24.00	0.54	54.19	267.69	19.30	387.93
1980	6.28	545	19.16	1.73	17.27	6.38	11.13	125.26
1990	3.49	458	6.09	0.96	9.60	18.56	4.48	18.98
2000	2.13	269	3.31	0.32	10.66	14.82	8.02	70.28
2010	1.31	405	7.27	0.26	6.76	61.31	12.74	179.02
2018	1.00	342	1.96	0.09	2.98	14.60	10.70	124.17

the so-called *expanding bull's eye effect* (Ashley et al., 2014; Ashley and Strader, 2016; Strader and Ashley, 2015) that emphasizes that 'targets' for natural disasters, i.e. the number of humans and the related infrastructure and possessions, are enlarging as the population in a region grows and spreads. As a result this expanding development also creates larger areas of potential impacts from natural hazards. For an adequate analysis or comparison of a natural disaster loss dataset that spans over several decades, it is therefore paramount to appropriately take into account changes in the exposure component through time.

To make the tornado losses in our dataset comparable over time, we apply a normalization approach to bring all loss data to the 2018 dollar level. Normalization techniques have been widely used in natural disaster studies to make loss data comparable, see e.g. Pielke et al. (2008), McAneney et al. (2009), Simmons et al. (2013) and Weinkle et al. (2018). Loss normalization is especially important given that our data spans a long horizon of almost 70 years.

The nominal loss $D_{t,i}$ for event i that is recorded in the SPC database in year t can be converted into a normalized loss amount $D_{2018,i}$ denominated in 2018 dollars as follows:

$$D_{2018,i} = D_{t,i} \times I_t \times \mathrm{WPC}_t \times P_{t,i}, \tag{1}$$

where I_t is the inflation adjustment to convert the money value in year t to the value in 2018, WPC_t is the real wealth per capita adjustment in year t and $P_{t,i}$ is the population adjustment for event i in year t.

To provide reliable normalized losses, we utilize the same data on inflation, real wealth per capita and population that have been used by Weinkle et al. (2018) for normalizing hurricane losses. As documented in Weinkle et al. (2018), the inflation adjustment is based on the implicit price deflator for gross domestic product for the years 1954–2018 provided by the U.S. Bureau of Economic Analysis (BEA). The nominal wealth estimates are based on the national current-cost net stock of fixed asset and consumer durable goods, also provided by the U.S. Bureau of Economic Analysis. The population adjustment is based on the total population size data of United States supplied by the United States Census Bureau.

To illustrate the applied procedure, consider the loss from the 300th tornado in 1978 that occurred in Kansas. The implicit price deflator of 2018 is 114.216 and the implicit price deflator of 1978 is 37.602. Hence, the inflation adjustment for 1978 is $I_{1978} = 114.216/37.602 = 3.037$. The national wealth in 1978 and 2018 are $8.037 trillion and $65.861 trillion, respectively. The wealth adjustment for 1978 is therefore $WPC_{1978} = 65.861/8.037 = 8.19$. The population size of United States in 2018 is 330.604 million and that for 1978 is 221.879 million, and therefore $P_{1978,300} = 1.490 = 330.604/221.879$. Hence, the overall adjustment for this 300th tornado in 1978 is

$$\begin{aligned} D_{2018,300} &= D_{1978,300} \times I_{1978} \times \mathrm{WPC}_{1978} \times P_{1978,300} \\ &= D_{1978,300} \times 3.037 \times 8.19 \times 1.490. \end{aligned}$$

2.3. Time trends in normalized loss data

In the next step we examine trends for normalized losses from tornadoes. Firstly, we calculate individual normalized loss data from 1954–2018 (for data prior to 1995, we use the mid-point of the interval of the loss category). Then we calculate the total loss from tornadoes for the United States as well as the average loss from an individual tornado event in the U.S. for each year. Table 1 provides descriptive statistics for normalized tornado loss events for the first year of our sample period 1954, for 1960, 1970, 1980, 1990, 2000, 2010 and for the final year of the sample period 2018. Given that losses from natural hazards such as tornadoes are typically heavy-tailed, average loss observations for a particular year are often driven by individual extreme events. However, the results in Table 1 seem to indicate that after an initial increase in the average magnitude of losses from tornado events between 1954 and the 1970/80s, there has been a substantial decline in the average normalized loss from tornadoes at the national level.

To further examine the issue, we regress the total annual loss per year as well as the average loss from a tornado event for each year against time, i.e. we run a simple linear regression model of the form

$$Loss_t = \alpha + \beta \times t \quad (t = 0, 1, \ldots, 64) \tag{2}$$

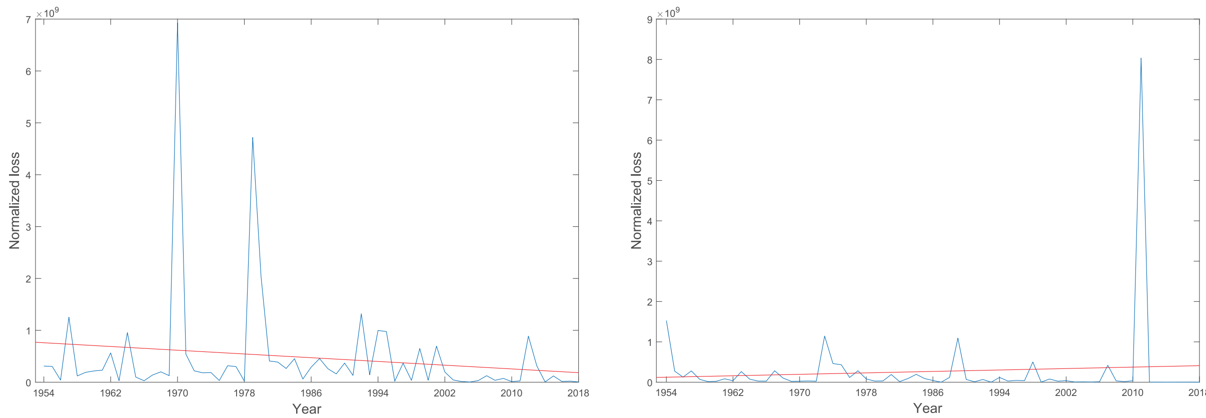

Fig. 4. Annual normalized total losses and fitted regression line for the states of Texas (left panel) and Alabama (right panel) for 1954–2018.

Table 2
Results for regressing total annual losses and annual average losses on time at the national level, for the state of Texas and for the state of Alabama.

Regressors		Annual loss	Annual loss of Texas	Annual loss of Alabama
alpha		2.34E+11	1.84E+10	−8.6E+09
	p-value	0.0033	0.185219	0.523131
	t-value	3.0514	1.339504	−0.64211
beta		−1.15E+08	−9008741	4471185
	p-value	0.0040	0.196601	0.510367
	t-value	−2.9869	−1.30511	0.662029
R-Square		0.1240	0.0263	0.0069
Regressors		Annual average loss	Annual average loss of Texas	Annual average loss of Alabama
alpha		463321515	1.74E+08	4.68E+08
	p-value	0.0006944	0.452416	0.107511
	t-value	3.5679154	0.756085	1.632746
beta		−227924.2	−82602.5	−230250
	p-value	0.0008988	0.478504	0.115312
	t-value	−3.48595	−0.71296	−1.59681
R-Square		0.1617	0.0080	0.1188

for the time period 1954 ($t = 0$) to 2018 ($t = 64$). The results are shown in Fig. 3 in which the left panel presents results for regressing the *total* normalized annual loss on t, while the right panel shows results for regressing the *average* normalized loss from an event each year on t. The analysis suggests a declining trend in the magnitude of total annual normalized losses as well as in the average normalized loss from a tornado event for the considered sample period.

Table 2 also reports estimated coefficients for the applied regression analysis. We find that at the national level both for total annual losses as well as for average annual losses the trend coefficients are negative and highly significant. Thus, our results suggest that when considering normalized losses from tornado events, the severity of total annual losses has significantly decreased throughout the considered sample period. Interestingly, despite an increase in the number of reported events from higher loss categories, see Fig. 2, we also find that there is a significantly decreasing trend in total normalized annual losses from tornadoes. Thus, our findings reiterate the results of Simmons et al. (2013) who emphasize the importance of normalizing loss data to draw adequate conclusions about the severity of natural hazards.

We also examine losses from tornadoes at the individual state level. The geographic dimension of changes in the risks from natural hazards or the impacts of climatic change has been pointed out in many studies, see, e.g., Moore and DeBoer (2019). We therefore decided to conduct the same trend analysis for total and average normalized annual losses for the 20 states in the U.S. with the highest frequency of tornado events throughout our sample period.[7] For 18 out of the 20 considered states we found a decreasing time trend for total annual normalized losses from tornado events, while only for two states, Alabama and Illinois, we observed an increasing trend. Furthermore, for all 20 states the time trend for the average normalized loss from a tornado event was decreasing throughout our sample period. In the following, we will only report the results for two of these states, namely Texas and Alabama, in more detail. Note that Texas was chosen, since it is the state with the highest number of events throughout our sample period. We also decided to include Alabama as one of two states with an increasing trend in the total annual normalized loss from tornado events.[8] Results for the conducted analysis are reported in Figs. 4 and 5 and Table 2.

Fig. 4 illustrates an decreasing trend in total annual normalized losses for the state of Texas, while it suggests that there has been an increasing trend in total losses for the state of Alabama for the 1954–2018 sample period. However, as indicated in Table 2 the estimated coefficients for the trend line are not significant and the explanatory power of the fitted model is quite low. Interestingly, for the average normalized annual losses from tornado events, we find a declining trend for both states as illustrated by Fig. 5. However, also here, the estimated slope coefficients are not significant. The observed results of Texas and Alabama confirm the geographic dimension of changes in the risk profile for the severity of tornado losses in different states (Moore and DeBoer, 2019).

3. Fitting probability distributions

Given our preliminary results on time trends in the severity of losses from tornadoes, as a next step we aim to fit appropriate severity distributions for the economic loss caused by an individual tornado through time. Hereby, we apply an approach that allows us to adequately deal with a mix of grouped data for the period 1954–1995 and actual loss estimates for the period 1996–2018.

Recall that prior to 1996, SPC loss data are recorded as grouped data with the ranges shown in Table 3. Following Eq. (1), we then normalized annual grouped loss data at the country level by using the adjustment factors from Weinkle et al. (2018). To make the loss intervals for each group consistent with the applied normalization procedure, we also normalized the group ranges, using country level normalization factors. For example, for the year 1978, the country

[7] These states included (in ascending order of tornado frequency) Texas, Florida, Mississippi, Iowa, Missouri, Alabama, Oklahoma, Kansas, Louisiana, Georgia, Illinois, Nebraska, Arkansas, Indiana, Wisconsin, Tennessee, Ohio, North Carolina, Kentucky, Michigan.

[8] Results for the other states are not presented here, but are available upon request to the authors.

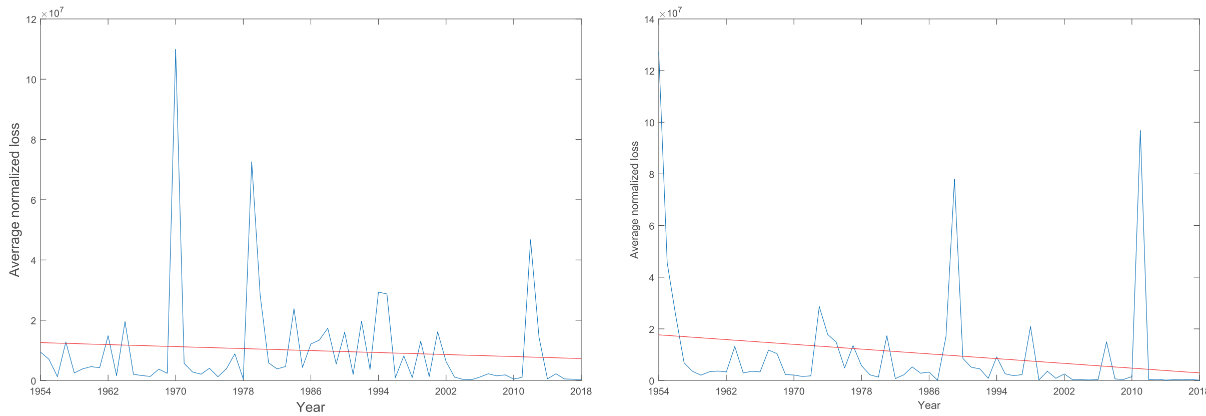

Fig. 5. Average normalized losses for tornado event in one year and fitted regression line for the states of Texas (left panel) and Alabama (right panel) for 1954–2018.

Table 3
Group range for data prior to 1996.

Group code	Group range
0	Unknown loss
1	0–\$50
2	\$50–\$500
3	\$500–\$5,000
4	\$5,000–\$50,000
5	\$50,000–\$500,000
6	\$500,000–\$5,000,000
7	\$5,000,000–\$50,000,000
8	\$50,000,000–\$500,000,000
9	More than \$500,000,000

level index is 8.1951. Hence, group 1 has range of 0–$\$50 \times 8.1951$, group 2 has range of $\$50 \times 8.1951$–$\$500 \times 8.1951$... group 8 has range of $\$50,000,000 \times 8.1951$–$\$500,000,000 \times 8.1951$ and group 9 has range of more than $\$500,000,000 \times 8.1951$.

3.1. Maximum likelihood method

Assume that we have a set of grouped data with a total of T observations which are divided into N groups. For group i, we have the lower limit z_{i-1} and upper limit z_i. To apply MLE to the grouped data, we need to define the predicted fraction of observations in each group as

$$P_i(y;\Phi) = F_y(z_i;\Phi) - F_y(z_{i-1};\Phi),$$

$F_y(z_{i-1};\Phi)$ denotes the cumulation distribution function of the chosen model with parameters Φ evaluated at z_{i-1} and where $i = 1, 2, \dots, N$. Then the likelihood function can be found as

$$L(y;\Phi) = T! \sum_{i=1}^{N} \frac{P_i(y;\Phi)^{T_i}}{T_i!}.$$

By applying numerical methods to maximize the above expression, the parameter vector, Φ can be obtained via the MLE estimator.

3.2. Generalized method of moments

Following Khemka et al. (2023), we apply a maximum likelihood estimator (MLE) (Hinkley and Cox, 1979; Klugman et al., 2012) as well as a generalized method of moments (GMM) estimator (Hajargasht et al., 2012) to fit a severity distribution for the grouped data.

In the following we use Φ to denote the vector of unknown parameters. The GMM estimator $\hat{\Phi}$ can be defined as

$$\hat{\Phi} = \arg\min_{\Phi} \mathbf{H}(\Phi)'\mathbf{W}\mathbf{H}(\Phi) \tag{3}$$

where $\mathbf{H}(\Phi)$ is a vector that measures the difference between sample moments and population moments, and $\mathbf{W}$ is a symmetric and positive definite weight matrix. The expected value of $\mathbf{H}(\Phi)$ is zero, i.e., $E[\mathbf{H}(\Phi)] = 0$. Changes in the weight matrix $\mathbf{W}$ may result in changes in the variance of the GMM estimator, and the optimal weight matrix is the one that provides an efficient GMM estimator with smallest asymptotic variance. Following Cameron and Trivedi (2005) and Hajargasht et al. (2012), we can use the inverse of the covariance matrix of the limiting distribution of $N^{1/2}\mathbf{H}(\Phi)$ to find the optimal weight matrix.

The GMM approach has been modified in Hajargasht et al. (2012) to estimate the parameters of the underlying distribution for grouped data. Specifically, the grouped dataset has the information of group limits (calculated based on Table 3 with normalization as described above), proportion of observations in each group and the mean value of each group.

In order to use the GMM approach, we assume that the total number of observations for tornado damage in our sample data is T and these data are classified into N groups. z_i, c_i and $\bar{y}_i$ are defined as the group limits, the proportion of observations and the mean value of group i. The number of observations in group i is T_i. The vector of differences between sample and population proportions in each group and the sample and population contributions to the overall mean is

$$\mathbf{H}(\Phi) = \begin{bmatrix} c_1 - k_1(\Phi) \\ \vdots \\ c_N - k_N(\Phi) \\ \tilde{y}_1 - \mu_1(\Phi) \\ \vdots \\ \tilde{y}_N - \mu_N(\Phi) \end{bmatrix} \tag{4}$$

where $k_i(\Phi)$ is the population proportion of observations in the ith group,

$$k_i(\Phi) = \int_{z_{i-1}}^{z_i} f(y;\Phi)dy \qquad i = 1,\ 2, \dots,\ N,$$

where $f(y;\Phi)$ is the probability density function for the severity model being estimated and $\tilde{y}_i$ is the contribution of the ith group mean to the overall mean, and is defined as

$$\tilde{y}_i = c_i \bar{y}_i.$$

The corresponding population quantity $\mu_i(\Phi)$ is defined as

$$\mu_i(\Phi) = \int_{z_{i-1}}^{z_i} y f(y;\Phi)dy \qquad i = 1, 2, \dots,\ N.$$

Intuitively, the identity matrix ($\mathbf{W} = \mathbf{I}$) is the simplest form of the weight matrix $\mathbf{W}$ in Eq. (3). However, from Eq. (4), it is clear that the last N terms of $\mathbf{H}(\Phi)$ are much larger than the first N terms. Hence, applying an identity matrix, which gives a substantial weight

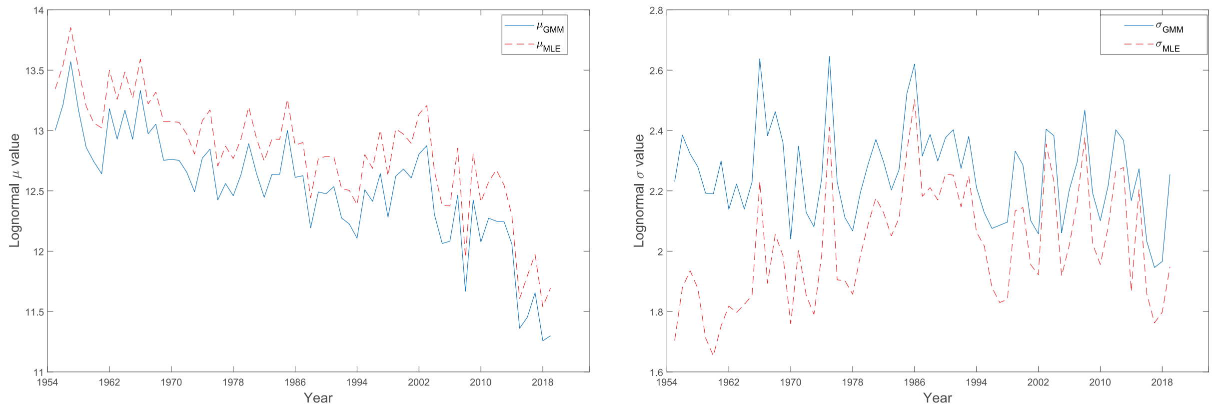

Fig. 6. Annual parameter estimates for μ (left panel) and σ (right panel) for the time period 1954–2018. Parameter estimates are reported for lognormal distributions with parameters estimated using the GMM and MLE approaches.

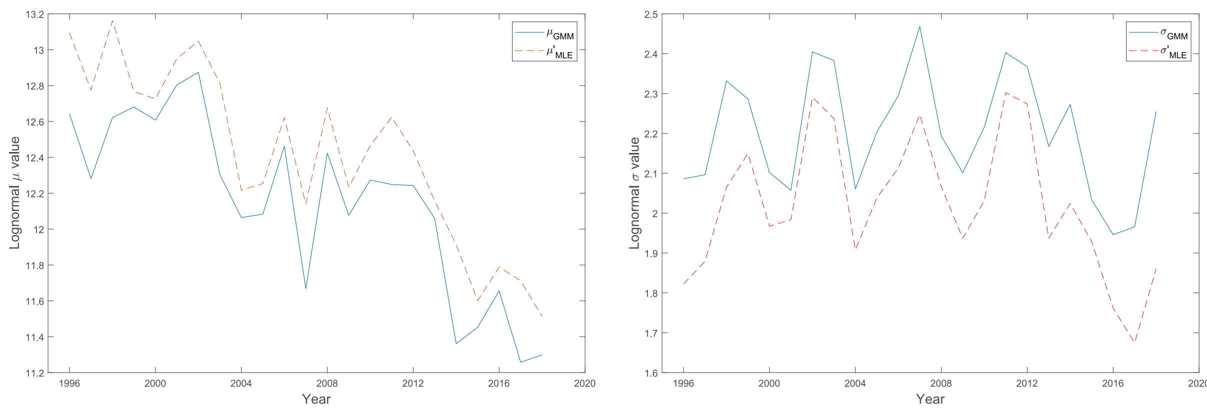

Fig. 7. Estimated values of μ (left panel)and σ (right panel) for fitted lognormal distributions to the grouped data via GMM and MLE. The series μ'_{MLE} (left panel) and σ'_{MLE} (right panel) illustrate the estimated values for μ and σ when a lognormal distribution is fitted to the individual loss data.

to the group mean terms, might not be appropriate. To overcome this issue, Hajargasht et al. (2012) state the optimal weight matrix as

$$\mathbf{W} = \begin{bmatrix} \mathbf{D}(\mathbf{w_1}) & -\mathbf{D}(\mathbf{w_3}) \\ -\mathbf{D}(\mathbf{w_3}) & \mathbf{D}(\mathbf{w_2}) \end{bmatrix} \tag{5}$$

where $\mathbf{D}(\mathbf{x})$ denotes a diagonal matrix with elements of the vector $\mathbf{x}$ on the main diagonal. $\mathbf{w_1}$, $\mathbf{w_2}$ and $\mathbf{w_3}$ are N-dimensional vectors with elements $w_{1i} = \mu_i^{(2)}/v_i$, $w_{2i} = k_i/v_i$ and $w_{3i} = \mu_i/v_i$. $\mu_i^{(2)}$ is defined as $\mu_i^{(2)} = \int_{z_{i-1}}^{z_i} y^2 f(y;\Phi)dy$ and $v_i = k_i\mu_i^{(2)} - \mu_i^2$.

The GMM objective function can then be shown as

$$\mathbf{H}(\Phi)'\mathbf{W}\mathbf{H}(\Phi) = \sum_{i=1}^{N} w_{1i}\left(c_i - k_i\right)^2 + \sum_{i=1}^{N} w_{2i}\left(\tilde{y}_i - \mu_i\right)^2 - 2\sum_{i=1}^{N} w_{3i}\left(c_i - k_i\right)\left(\tilde{y}_i - \mu_i\right). \tag{6}$$

By applying numerical methods to minimize the above expression, we can find the GMM estimator for the parameter vector, Φ.

3.3. Results at the national level

We first use calendar years to create an annual dataset for the period 1954–2018. Specifically, we use the grouped data from 1954 to 1995 and aggregate the individual loss amounts for each event across each calendar year from 1996 to 2018. Then, for each yearly grouped dataset from 1954 to 2018, we use MLE as well as the GMM approach described above to estimate the parameter values for a fitted lognormal distribution. To further test the accuracy of our approach, we grouped the data after 1995 by using the normalized group borders and use MLE and the GMM approach to estimate the parameters of a lognormal distribution fitted to the grouped data. Estimated values for the location parameter μ and scale parameter σ for data from 1954–2018 are provided in Fig. 6.

Fig. 6 illustrates that the two approaches provide qualitatively similar results. For both approaches μ appears to be decreasing through time, while σ seems to increase between 1954 and the mid 1980s and shows an overall decreasing trend afterwards. Our results also suggest that the GMM approach seems to yield slightly higher estimates for μ and σ in comparison to the MLE approach. This is true in particular for the period 1954 to 1995 when only grouped data are available. We also find that the differences between the estimates for μ are less pronounced for the period 1996 to 2018 when individual loss data are available.

We further compared these estimated results for the grouped data from 1996 to 2018 with results via the MLE approach by fitting individual data from 1996 to 2018 in Fig. 7. The figure shows that the GMM approach can produce parameter estimates that are very close to the results of using an MLE approach for the individual data. Using individual data and the estimated parameters provided by the two approaches, we obtained log likelihood values that are very similar, which suggests that the GMM method based on grouped data can produce quite accurate parameter estimation.

Using parameters estimated by the GMM approach year by year, we plot normalized loss distributions in Fig. 8. The figure clearly shows the large impact of tornadoes in 1956 and 1965 that make tornado losses in recent years to appear small. Our results are broadly consistent with the results presented by Simmons et al. (2013) despite some differences in the method that we use. While our normalization method allows for the growth in loss exposure due to the development in inflation,

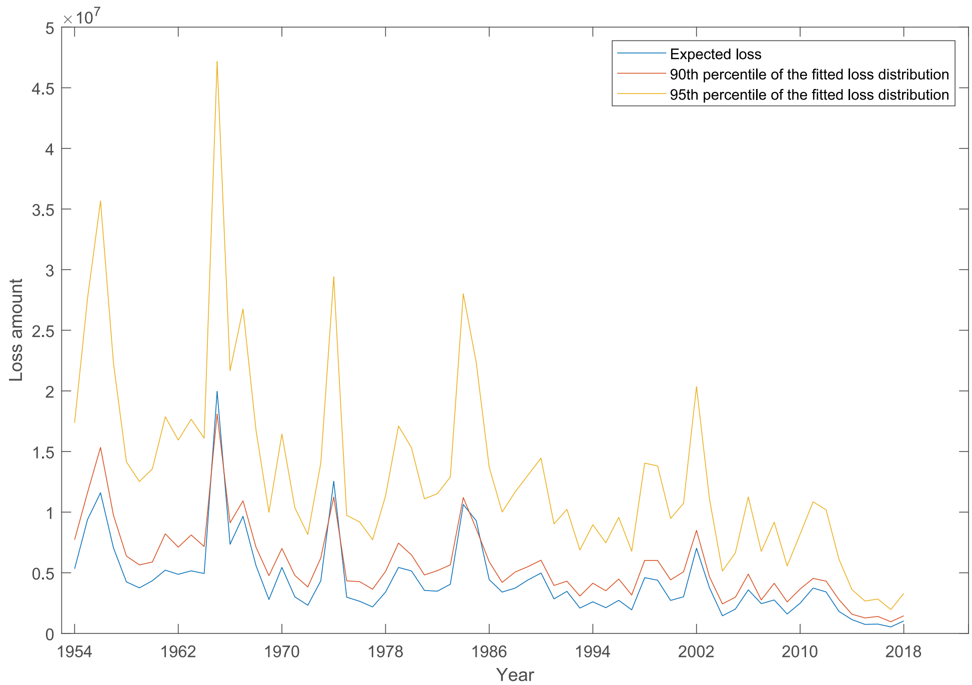

Fig. 8. Expected loss as well as 90th and 95th percentile of the loss distribution from 1954 to 2018 by using the results of GMM approach.

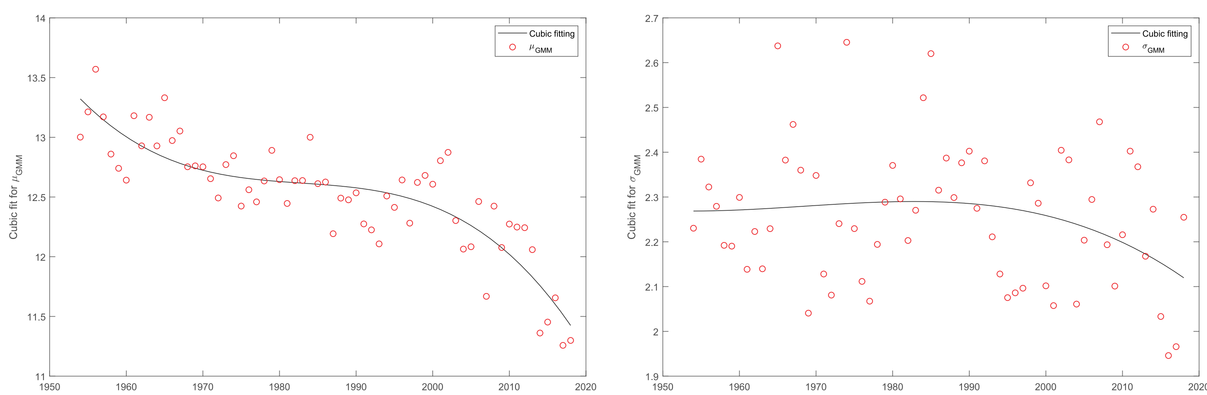

Fig. 9. Cubic polynomial fit to estimated annual parameter estimates for μ (left panel) and σ (right panel) of a lognormal distribution based on the applied GMM approach.

population and wealth, Simmons et al. (2013) allows for only the impact of inflation. In addition, Simmons et al. (2013) utilize an *ad hoc* approach to obtain average losses while we provide a statistically consistent method that allows to estimate the whole distribution of tornado losses. These differences in methods are translated to more accurate estimation of loss distributions and lower levels of normalized tornado losses in recent years.

Next we examine time trends in the estimated parameters for the fitted lognormal distributions for economic loss caused by an individual tornado. For both the annual GMM estimates of μ and σ, we fit a cubic spline to identify changes across time in the estimated severity distribution.[9] Fig. 9 illustrates the annual estimates of the parameters μ and σ as well as the fitted spline function. The results clearly confirm the decreasing trend in μ and suggest an initially increasing and then decreasing trend in the estimates for σ through time.[10]

Overall, these results seem to suggest that the magnitude of losses from individual tornado events has decreased considerably for the sample period from 1954–2018 (we observe this trend in Fig. 8). Note, however, that both μ and σ impact in different ways on the shape of the lognormal distribution. For example, the median of a lognormal distribution is simply $\exp(\mu)$, while the mean ($\exp(\mu+0.5\sigma^2)$) as well as the quantiles of the distribution depend both on μ and σ. In particular, high values of the scale parameter σ can lead to extreme values for higher quantiles of the loss distribution. Table 4

[9] To further verify our findings, we applied generalized additive models for location, scale, and shape to fit all of the data from every year into a single lognormal distribution, finding that the location and scale parameters exhibit a decreasing trend over time.

[10] Note that the fit of the cubic spline model is highly significant for μ, where all coefficients are significant at the 1% level and the model yields a high explanatory power of $R^2 = 0.7417$. For σ due to a high variation in the estimated coefficients, the fit of the cubic spline model yields insignificant coefficients and a much lower coefficient of determination of $R^2 = 0.0823$. Detailed estimation results are not reported here but are available upon request to the authors.

Table 4
Descriptive statistics for fitted total annual loss of 1954, 1960, 1970, 1980, 1990, 2000, 2010 and 2018 by using GMM.

Year	μ_{GMM}	σ_{GMM}	Mean (in millions)	Median (in millions)	90th percentile (in millions)	95th percentile (in millions)	Standard deviation (in millions)	Skewness	Kurtosis (in millions)
1954	13.00	2.23	5.3290	0.4431	7.7232	17.3662	38.8762	1758.016	444.1545
1960	12.64	2.30	4.3430	0.3090	5.8830	13.5628	37.0214	2796.988	1537.6400
1970	12.75	2.35	5.4420	0.3455	7.0044	16.4384	51.9867	3930.601	3817.4338
1980	12.65	2.37	5.1511	0.3102	6.4719	15.3128	51.8785	4603.046	5821.1714
1990	12.53	2.40	4.9781	0.2779	6.0385	14.4535	54.0907	5776.076	10674.4112
2000	12.61	2.10	2.7191	0.2987	4.4156	9.4754	15.0121	767.7695	48.2949
2010	12.27	2.22	2.4914	0.2140	3.6607	8.1877	17.5953	1596.131	342.9836
2018	11.30	2.25	1.0259	0.0807	1.4524	3.2948	7.9056	2069.768	687.3729

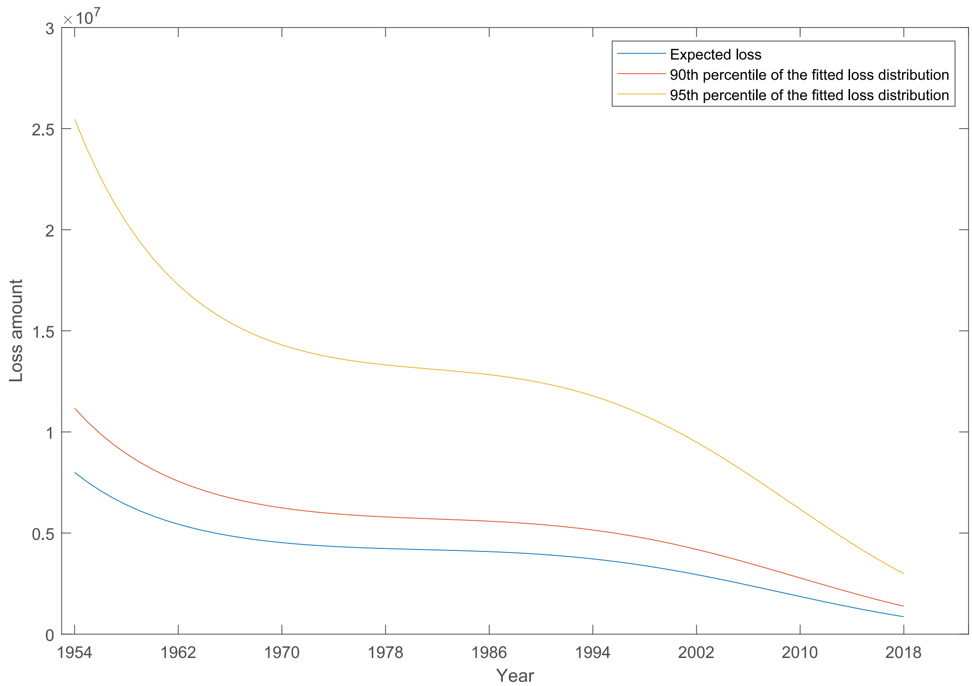

Fig. 10. Expected loss as well as 90th and 95th percentile of the loss distribution from 1954 to 2018 by using the results of GMM approach (Cubic fit).

provides additional information on the estimated loss distribution for the severity of tornado events at different points in time, namely, at the beginning of the sample period in 1954, for every decade, i.e. 1960, 1970, 1980, 1990, 2000, 2010, and at the end of our sample period in 2018. The table illustrates that the mean and median as well as the higher quantiles of normalized losses from tornado events, after an initial increase towards the 1970s and 1980s, have reduced significantly over the sample period. The estimated mean for loss events in 1954 was around \$5.33 million, while it was only \$1.03 million in 2018. The normalized median loss was \$0.44 in 1954 and only \$0.08 in 2018. Note that the declining trend in losses from tornadoes is directly related to normalizing the data. As illustrated in Table 1 the applied normalization factors for losses from earlier years of the sample period are quite substantial, e.g. 53.19 for loss observations from 1954, 38.60 for losses from tornadoes in 1960, etc. However, ignoring adjustment factors related to inflation, wealth per capita and population growth would lead to incorrect estimates of trends in the loss distribution, since losses over a 70 year period are not comparable unless they are normalized in an appropriate manner. As illustrated in Section 2.3, for our normalization procedure we follow Weinkle et al. (2018), using a method widely accepted in the current literature on assessing losses from natural hazards. The use of normalized data then allows us to adequately analyse patterns and trends in the severity of hurricanes in the U.S.

Based on the cubic spline fit to the estimated parameters for the severity distribution, we provide a plot of the expected loss as well as the 90th and 95th percentile of the loss distribution for the 1954 to 2018 sample period. Fig. 10 shows the substantial drop in the expected normalized loss from a tornado over the considered time period. In 2018 dollar values the expected loss from a tornado was approximately $\$8,000,000$ in 1954, while the expected loss has dropped to less than $\$1,000,000$ in 2018. Results are even more pronounced for higher quantiles: while the 95th percentile of the estimated loss distribution was greater than $\$15,000,000$ in 1954, recent estimates would be around $\$3,500,000$. We have included Figs. 11 and 12 to demonstrate the trend of the expected normalized loss from a tornado event in Texas and Alabama over the considered time period. Overall, we find that the estimated distribution for losses from tornadoes has become less skewed and heavy-tailed through time. We also demonstrated the decreasing trend in mean loss per year and total loss per year for different F-scale categories in Figs. 13 and 14.

4. Conclusions

In this paper, we illustrate a method that helps to estimate the loss distribution for individual tornadoes in the U.S., using grouped data together with individual loss data in the SPC dataset. Since predictions about tornado frequency and severity are sometimes contradictory, our method provides an important tool for the estimation of the individual tornado loss distribution based on available data.

Our findings suggest that loss normalization plays an important role in the estimation of the individual tornado loss distribution. Without

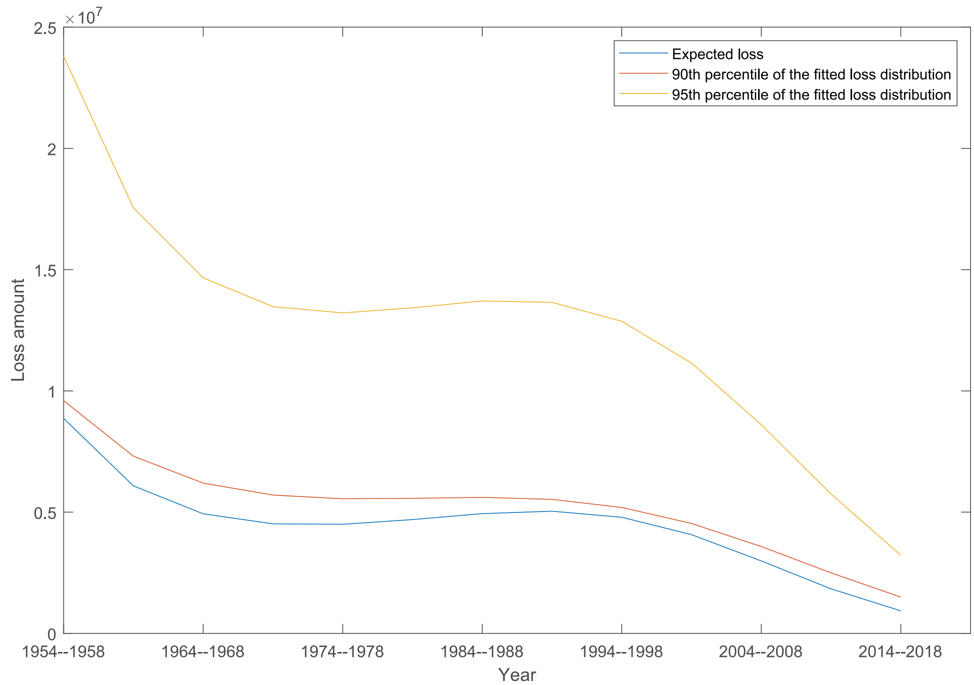

Fig. 11. Percentile of loss distribution of Texas from 1954 to 2018 by using the results of GMM approach (Cubic fit).

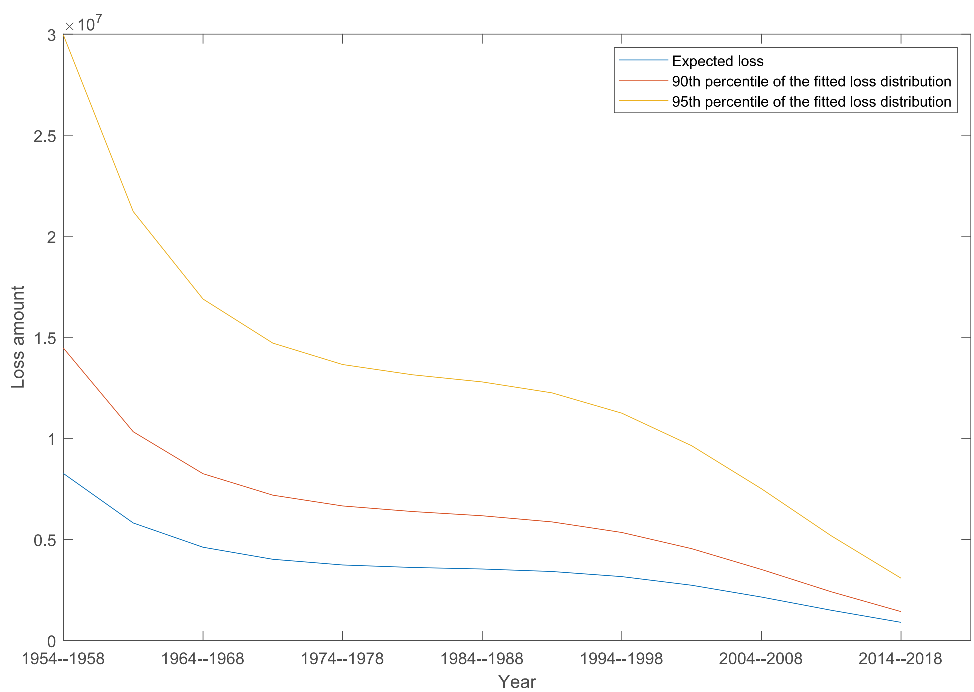

Fig. 12. Percentile of loss distribution of Alabama from 1954 to 2018 by using the results of GMM approach (Cubic fit).

normalization, losses generally increase over time due to growth of population and wealth, higher loss exposure as a result of the expanding bull's eye effect, and inflation rather than more intense tornadoes. We also find that the expected normalized losses decrease over time, consistent with the improvements in building standards and the results reported by Tippett (2014) on tornado frequency. As found by Tippett (2014) and confirmed by our paper, the frequency of F1 tornadoes increases over time while that of F2+ tornadoes decreases over time. The average losses from severe tornadoes are then decreasing in time, while for less intensive tornadoes, building standard improvements would work to reduce tornado losses. As a result, the expected tornado losses are decreasing in time. Although the expected loss has a decreasing trend, loss variance is time varying and makes the loss events in 2011 quite possible (90th percentile of loss events in 2011 is 7.346 million and 95th percentile of loss events in 2011 is 19.202 million).

We also apply the method to two states, Texas and Alabama, in which tornadoes occur most frequently. Our findings suggest that the expected loss caused by an tornado in Alabama is decreasing in time while the expected loss in Texas is non-linear in time. These results corroborate findings by Boruff et al. (2003) who found a declining trend in tornado deaths and injuries and are consistent with the findings by Moore and DeBoer (2019) that tornado losses can have different

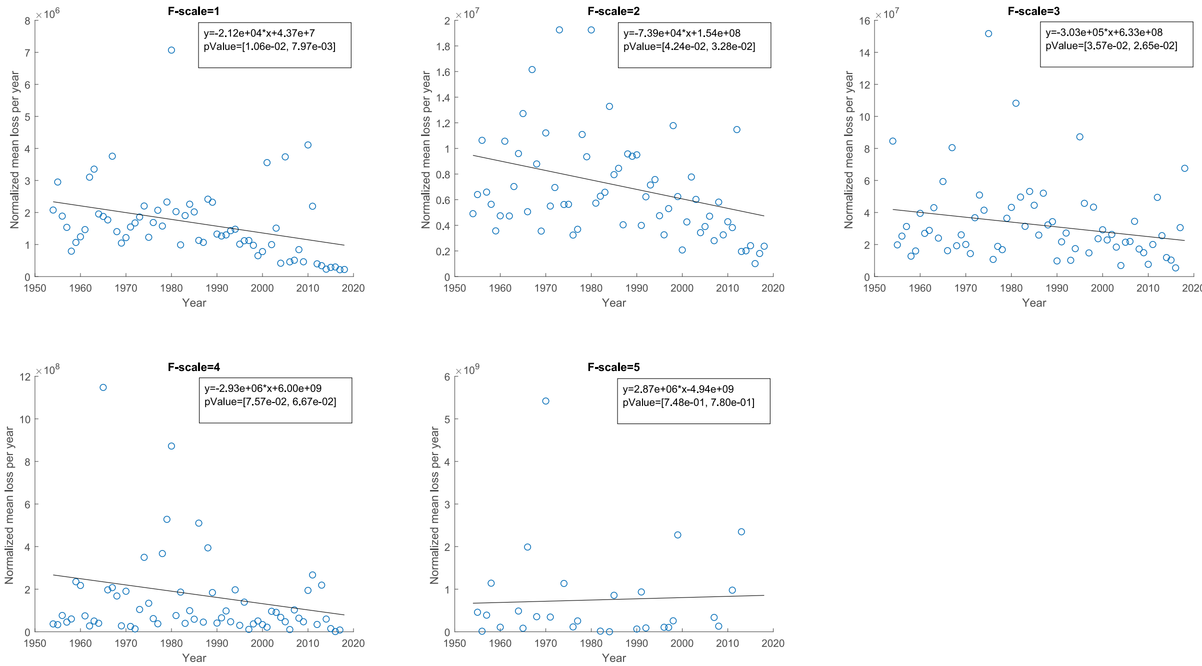

Fig. 13. Normalized mean loss per year for each F-scale category. The trend line is based on the all normalized loss events truncated at $1000.

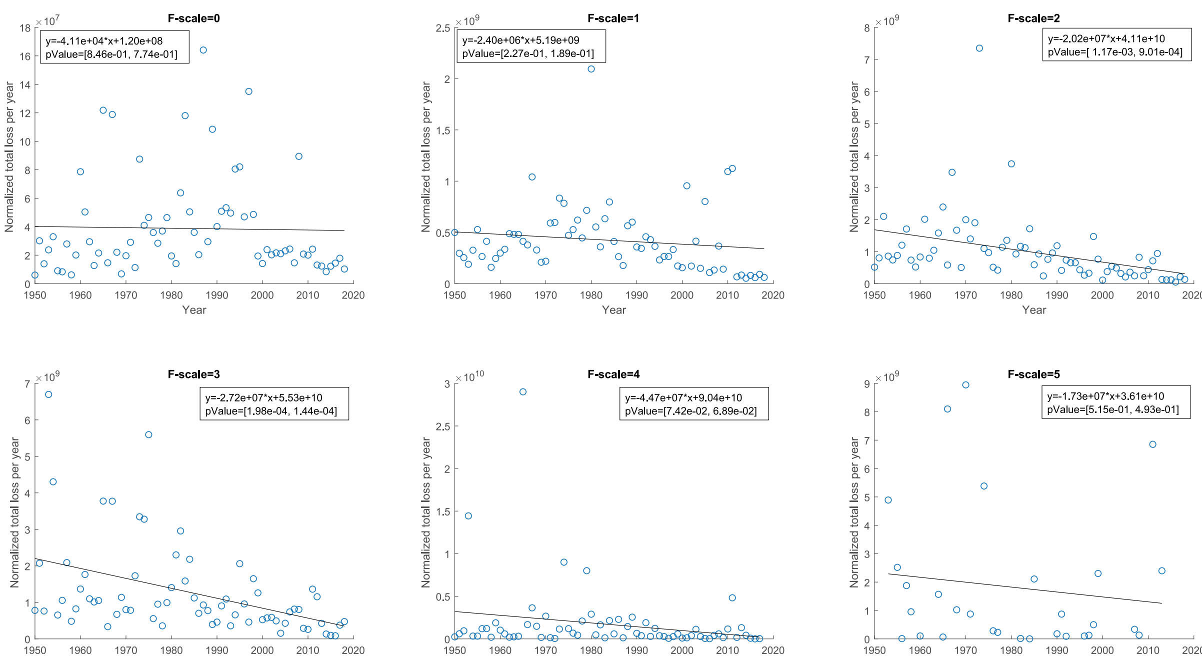

Fig. 14. Normalized total loss per year for each F-scale category.

trends in different states. Different from previous studies, we examine the dynamics of both the mean and the volatility for the log of tornado losses and find that both of these parameters have decreased in recent decades, leading to the decrease in expected tornado losses. These results also suggest that tornado losses have trended downwards in their average value and also in their variation. In addition, we examine high quantiles of the estimated loss distribution and find that the distribution has become less skewed and heavy-tailed over time.

Overall, our results suggest a downward trend in tornado losses for the U.S. as a nation, while tornado losses at the state level can have upward or downward trends. This suggests that policies that aim to mitigate tornado losses should be state specific. Tornado data at the state level are much more limited, and the method presented in this paper that allows to use grouped data together with individual event data is a valuable tool for the examination of state specific tornado loss mitigation.

CRediT authorship contribution statement

Jinhui Zhang: Methodology, Data curation, Software, Writing – original draft, Visualization, Investigation. **Stefan Trück:** Validation, Writing – review & editing. **Chi Truong:** Conceptualization, Data curation, Writing – original draft. **David Pitt:** Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Description of SPC database

The SPC dataset is provided by the U.S. National Weather Service. It covers tornado losses insured in 52 states over the period 1954–2018. It has:

- Number of tornadoes for each state for each year (variable *om*). A tornado that affects several states will enter the database several times with the same *om* and different states (*st*).
- Number of states affected by a tornado (ns). 63,229 tornadoes occurred in one state, 1550 occurred in two states and 45 tornadoes occurred in 3 states.
- F-scale (variable *mag*) of tornadoes that is based on windspeed, hail size. F-scale $\in \{-9, 0, 1, 2, 3, 4, 5\}$ where −9 indicates unknown scale. Higher F-scale indicates stronger tornadoes. Note that 1864 records of the initially unknown scale have been converted to some scale based on property losses. These records are marked by variable fc that receives value 1 when the scale is modified and 0 otherwise. tornadoes with modified scales occur over the period 1953–1982.
- Property loss in dollar amount ($loss$). Prior to 1996, losses are recorded in categories: 0 or blank indicates unknown loss; 1 means being less than 50, 2 means \$50–\$500, 3 means \$500–\$5000, 4 means \$5000–\$50,000, …, 8 means \$50,000,000–\$500,000,000, and 9 means more than \$5,000,000,000.
  From 1996 to 2015, property loss amounts are rounded and recorded in terms of million. From 2016, property loss amounts are rounded and recorded in actual dollar amounts.

References

Agee, E., Childs, S., 2014. Adjustments in tornado counts, F-scale intensity, and path width for assessing significant tornado destruction. J. Appl. Meteorol. Climatol. 53 (6), 1494–1505.

Ashley, W.S., Strader, S.M., 2016. Recipe for disaster: How the dynamic ingredients of risk and exposure are changing the tornado disaster landscape. Bull. Am. Meteorol. Soc. 97 (5), 767–786.

Ashley, W.S., Strader, S., Rosencrants, T., Krmenec, A.J., 2014. Spatiotemporal changes in tornado hazard exposure: The case of the expanding bull's-eye effect in Chicago, Illinois. Weather Clim. Soc. 6 (2), 175–193.

Auffhammer, M., 2018. Quantifying economic damages from climate change. J. Econ. Perspect. 32 (4), 33–52.

Boero, R., Bianchini, L., Pasqualini, D., 2015. Vulnerability and adaptation to severe weather events in the American southwest. Weather Clim. Extrem. 8, 12–25.

Boruff, B.J., Easoz, J.A., Jones, S.D., Landry, H.R., Mitchem, J.D., Cutter, S.L., 2003. Tornado hazards in the United States. Clim. Res. 24 (2), 103–117.

Botzen, W.J.W., Deschenes, O., Sanders, M., 2019. The economic impacts of natural disasters: A review of models and empirical studies. Rev. Environ. Econ. Policy 13 (2), 167–188.

Brooks, H.E., Carbin, G.W., Marsh, P.T., 2014. Increased variability of tornado occurrence in the United States. Science 346 (6207), 349–352.

Brooks, H.E., Doswell, C.A., 2001. Normalized damage from major tornadoes in the United States: 1890–1999. Weather Forecast. 16 (1), 168–176.

Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press.

Cusack, S., 2014. Increased tornado hazard in large metropolitan areas. Atmos. Res. 149, 255–262.

Diaz, J., Joseph, M.B., 2019. Predicting property damage from tornadoes with zero-inflated neural networks. Weather Clim. Extrem. 25, 100216.

Diaz, D., Moore, F., 2017. Quantifying the economic risks of climate change. Nature Clim. Change 7, 774–882.

Diffenbaugh, N.S., Scherer, M., Trapp, R.J., 2013. Robust increases in severe thunderstorm environments in response to greenhouse forcing. Proc. Natl. Acad. Sci. 110 (41), 16361–16366.

Edwards, R., LaDue, J.G., Ferree, J.T., Scharfenberg, K., Maier, C., Coulbourne, W.L., 2013. Tornado intensity estimation: Past, present, and future. Bull. Am. Meteorol. Soc. 94 (5), 641–653.

Elsner, J.B., Michaels, L.E., Scheitlin, K.N., Elsner, I.J., 2013. The decreasing population bias in tornado reports across the central plains. Weather Clim. Soc. 5 (3), 221–232.

Esteves, L.S., 2013. Consequences to flood management of using different probability distributions to estimate extreme rainfall. J. Environ. Manag. 115, 98–105.

Fan, F., Pang, W., 2019. Stochastic track model for tornado risk assessment in the US. Front. Built Environ. 5, 37.

Gall, M., Borden, K.A., Cutter, S.L., 2009. When do losses count? Six fallacies of natural hazards loss data. Bull. Am. Meteorol. Soc. 90 (6), 799–810.

Guo, L., Wang, K., Bluestein, H.B., 2016. Variability of tornado occurrence over the continental United States since 1950. J. Geophys. Res.: Atmos. 121 (12), 6943–6953.

Hajargasht, G., Griffiths, W.E., Brice, J., Rao, D.P., Chotikapanich, D., 2012. Inference for income distributions using grouped data. J. Bus. Econom. Statist. 30 (4), 563–575.

Hinkley, D.V., Cox, D., 1979. Theoretical Statistics. Chapman and Hall/CRC.

Hoeppe, P., 2016. Trends in weather related disasters–consequences for insurers and society. Weather Clim. Extrem. 11, 70–79.

Jung, C., Schindler, D., 2021. Does the winter storm-related wind gust intensity in Germany increase under warming climate? A high-resolution assessment. Weather Clim. Extrem. 33, 100360.

Keighley, T., Longden, T., Mathew, S., Trück, S., 2018. Quantifying catastrophic and climate impacted hazards based on local expert opinions. J. Environ. Manag. 205, 262–273.

Khemka, G., Pitt, D., Zhang, J., 2023. On fitting probability distribution to univariate grouped actuarial data with both group mean and relative frequencies. N. Am. Actuar. J. 27 (1), 185–205.

Klugman, S.A., Panjer, H.H., Willmot, G.E., 2012. Loss Models: From Data to Decisions, vol. 715. John Wiley & Sons.

Knutson, T.R., McBride, J.L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J.P., Srivastava, A., Sugi, M., 2010. Tropical cyclones and climate change. Nat. Geosci. 3 (3), 157–163.

Liang, M.S., Julius, S., Dong, Z., Neal, J., Yang, Y.J., 2020. Assessing and managing design storm variability and projection uncertainty in a changing coastal environment. J. Environ. Manag. 264, 110494.

McAneney, J., Chen, K., Pitman, A., 2009. 100 years of Australian bushfire property losses: Is the risk significant and is it increasing? J. Environ. Manag. 90 (8), 2819–2822.

Mendes-Da-Silva, W., Lucas, E.C., de França Carvalho, J.V., 2021. Flood insurance: The propensity and attitudes of informed people with disabilities towards risk. J. Environ. Manag. 294, 113032.

Moore, T.W., DeBoer, T.A., 2019. A review and analysis of possible changes to the climatology of tornadoes in the United States. Prog. Phys. Geogr. Earth Environ. 43 (3), 365–390.

Outten, S., Sobolowski, S., 2021. Extreme wind projections over Europe from the Euro-CORDEX regional climate models. Weather Clim. Extrem. 33, 100363.

Pielke, R.A., Gratz, J., Landsea, C.W., Collins, D., Saunders, M.A., Musulin, R., 2008. Normalized hurricane damage in the United States: 1900–2005. Nat. Hazard. Rev. 9 (1), 29–42.

Pitt, D., Trück, S., van den Honert, R., Wong, W.W., 2020. Modeling risks from natural hazards with generalized additive models for location, scale and shape. J. Environ. Manag. 275, 111075.

Ripberger, J.T., Jenkins-Smith, H.C., Silva, C.L., Czajkowski, J., Kunreuther, H., Simmons, K.M., 2018. Tornado damage mitigation: Homeowner support for enhanced building codes in Oklahoma. Risk Anal. 38 (11), 2300–2317.

Ross, H., Carter, R.W., 2011. Natural disasters and community resilience. Australas. J. Environ. Manag. 18 (1), 1–5.

Ryan, E., 2018. Florida's Tornado Climatology: Occurrence Rates, Casualties, and Property Losses.

Sillmann, J., Thorarinsdottir, T., Keenlyside, N., Schaller, N., Alexander, L.V., Hegerl, G., Seneviratne, S.I., Vautard, R., Zhang, X., Zwiers, F.W., 2017. Understanding, modeling and predicting weather clim. extrem.: Challenges and opportunities. Weather Clim. Extrem. 18, 65–74.

Simmons, K.M., Kovacs, P., Kopp, G.A., 2015. Tornado damage mitigation: Benefit–cost analysis of enhanced building codes in Oklahoma. Weather Clim. Soc. 7 (2), 169–178.

Simmons, K., Sutter, D., 2013. Economic and Societal Impacts of Tornadoes. Springer Science & Business Media.

Simmons, K.M., Sutter, D., Pielke, R., 2013. Normalized tornado damage in the United States: 1950–2011. Environ. Hazard. 12 (2), 132–147.

Strader, S.M., Ashley, W.S., 2015. The expanding bull's-eye effect. Weatherwise 68 (5), 23–29.

Strader, S.M., Ashley, W.S., Pingel, T.J., Krmenec, A.J., 2017. Projected 21st century changes in tornado exposure, risk, and disaster potential. Clim. Change 141 (2), 301–313.

Sutter, D., DeSilva, D., Kruse, J., 2009. An economic analysis of wind resistant construction. J. Wind Eng. Ind. Aerodyn. 97 (3–4), 113–119.
Tippett, M.K., 2014. Changing volatility of US annual tornado reports. Geophys. Res. Lett. 41 (19), 6956–6961.
Tippett, M.K., Allen, J.T., Gensini, V.A., Brooks, H.E., 2015. Climate and hazardous convective weather. Curr. Clim. Chang. Rep. 1 (2), 60–73.
Tippett, M.K., Lepore, C., Cohen, J.E., 2016. More tornadoes in the most extreme US tornado outbreaks. Science 354 (6318), 1419–1423.
Travis, W.R., 2014. Weather and climate extremes: Pacemakers of adaptation? Weather Clim. Extrem. 5, 29–39.
Wang, S., Mu, L., Qi, M., Yu, Z., Yao, Z., Zhao, E., 2021. Quantitative risk assessment of storm surge using GIS techniques and open data: A case study of Daya Bay Zone, China. J. Environ. Manag. 289, 112514.
Weinkle, J., Landsea, C., Collins, D., Musulin, R., Crompton, R.P., Klotzbach, P.J., Pielke, R., 2018. Normalized hurricane damage in the continental United States 1900–2017. Nat. Sustain. 1 (12), 808–813.
Zhang, F., 2021. Evaluating public organization performance under extreme weather events: Does organizational adaptive capacity matter? J. Environ. Manag. 296, 113388.