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Quantifying Uncertainty and Variable Sensitivity within the U.S. Billion-dollar Weather and Climate Disaster Cost Estimates

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Abstract

Research examining natural disaster costs on social and economic systems is substantial. However, there are few empirical studies that seek to quantify the uncertainty and establish confidence intervals surrounding natural disaster cost estimates (ex-post). To better frame the data limitations associated with natural disaster loss estimates, a range of losses can be evaluated by conducting multiple analyses and varying certain input parameters to which the losses are most sensitive. This paper contributes to the literature by examining new approaches for better understanding the uncertainty surrounding three U.S. natural disaster cost estimate case studies, via Monte Carlo simulations to quantify the 95%, 90% and 75% confidence intervals. This research also performs a sensitivity analysis for one of the case studies examining which input data variables and assumptions are the most sensitive and contribute most to the overall uncertainty of the estimate.

The Monte Carlo simulations for all three of the natural disaster events examined provide additional confidence in the U.S. Billion-dollar weather and climate disaster loss estimate report (NCDC 2014), since these estimates are within the confidence limits and near the mean and median of the example simulations. The normalized sensitivity analysis of Hurricane Ike damage costs determined that commercial losses in Texas are the most sensitive to assumption variability. Therefore, improvements in quantifying the commercial insurance participation rate for Texas will result in the largest reduction of uncertainty in the total loss estimate for Hurricane Ike. Further minimization of uncertainty would continue with improved measurement of subsequent cost parameters in order of descending sensitivity.

Keywords: natural disasters; costs; losses; uncertainty; statistics of extreme events; sensitivity

1. Introduction

The United States and its economy are challenged by weather and climate-related disasters that impart large social and economic costs (Gall et al. 2011, Field et al. 2012, NCA 2014). Consequently, natural disaster cost estimates are referenced by a wide variety of users for varying purposes. However, there are notable differences in the uncertainty surrounding different natural disaster types reflecting the quality of the data available, methodology and assumptions (Kron et al. 2012). For example, in the United States drought and flooding events have higher potential uncertainty values around their loss estimates due to less coverage of insured assets (Smith and Katz 2013). Conversely, severe local storm events have lower potential uncertainty around their loss estimates due to more complete insurance coverage of wind and hail damage.

Research examining natural disaster costs on social and economic systems is substantial. Example studies include: normalizing disaster loss trends over space and time using population and wealth variables (Downton et al. 2005, Pielke et al. 2008, Barthel and Neumayer 2012, Simmons et al. 2013), examining how developing countries and smaller economies often suffer more greatly due to natural disaster impacts (World Bank 2005, Hallegatte and Dumas 2009, IPCC 2014), and exploring how developed countries have more capacity to rebound from natural disasters impacts due to their wealth and financial systems (Rasmussen 2004, Toya and Skidmore 2007, Cavallo and Noy 2009). Other research seeks to quantify total, direct losses (i.e., both insured and uninsured) resulting from specific natural hazard events using independent estimation methodologies (ECLAC 2003, Munich Re 2014, Swiss Re 2014). However, there are few empirical studies that seek to quantify the uncertainty and confidence intervals surrounding natural disaster cost estimates (ex-post). To better frame the data limitations associated with natural disaster loss estimates, a range of losses can be evaluated by conducting multiple analyses and varying certain input parameters to which the losses are most sensitive (FEMA 2015). This paper contributes to the literature by examining new approaches for better understanding the uncertainty surrounding three U.S. natural disaster cost estimate case studies, by running Monte Carlo simulations to quantify the 95%, 90% and 75% confidence intervals. This research also performs a sensitivity analysis for one of the case studies examining which input data variables and assumptions are the most sensitive and contribute most to the overall cost uncertainty of the estimate.

The foundation for this research is the U.S. Billion-dollar Weather and Climate Disaster report developed by the National Oceanic and Atmospheric Administration's National Climatic Data Center. This analysis quantifies the loss from numerous weather and climate disasters including: tropical cyclones, floods, drought & heat waves, severe local storms (i.e., tornado, hail, straight-line wind damage), wildfires, crop freeze events and winter storms (NCDC 2014). These loss estimates reflect direct effects of weather and climate events (i.e., not including indirect effects) and constitute total losses (i.e., both insured and uninsured). The insured and uninsured direct loss components include: physical damage to residential, commercial and government/municipal buildings, material assets within a building, time element losses (i.e., businesses interruption), vehicles, boats, offshore energy platforms, public infrastructure (i.e., roads, bridges, buildings) and agricultural assets (i.e., crops, livestock, timber). These loss assessments do not take into account losses to natural capital/assets, healthcare related losses, or values associated with loss of life. Only weather and climate disasters which cause losses of ≥ 1 billion-dollars in calculated damage including Consumer Price Index (CPI) inflation adjustment are included in this dataset (**Table 1**). While this threshold is arbitrary, these billion-dollar events account for roughly 80% of the total U.S. losses for all combined severe weather and climate events (Munich Re 2012, NCDC 2014).

These natural disaster cost assessments require input from a variety of public and private data sources including: the Insurance Services Office (ISO) Property Claim Services (PCS), Federal Emergency Management Agency (FEMA) National Flood Insurance Program (NFIP) and Presidential Disaster Declaration (PDD) assistance, and the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) & Risk Management Agency (RMA), among others. Each of these data sources provides unique information as part of the overall disaster loss assessment. Previous research analyzed the suitability of these data sources including trends, data accuracy and potential biases (Smith and Katz 2013) and found the U.S. Billions-dollar disaster estimates had a consistent underestimation bias of roughly 10 to 15%. This bias was corrected during a reanalysis of the disaster event loss data to reflect new loss totals (NCDC 2014). However, there are still uncertainty envelopes encompassing these reanalyzed disaster loss estimates, which this research will offer new approaches for quantifying.

An outline of the paper is as follows. Primary insurance loss data and assumptions for natural disaster loss estimates are described in Section 2. Next, a Monte Carlo simulation method for estimating uncertainty surrounding disaster loss estimates, focusing on specific disaster examples, is presented in Section 3. A sensitivity analysis examining which data and assumptions are most important within one of the three disaster case study is examined in Section 4. Finally, Section 5 contains a discussion and conclusions on the uncertainty and sensitivity analysis results, to improve the U.S. billion-dollar disaster cost analysis.

Disaster Type	Number of Events	Percent Frequency	CPI-adjusted Losses ($ billions)	Percent of Total Loss	Average Event Cost ($ billions)
Drought	21	12.4	199	19.1	9.5
Flooding	19	11.2	86	8.3	4.5
Freeze	7	4.1	25	2.4	3.6
Severe Storm	65	38.2	143	13.7	2.2
Tropical Cyclone	34	20.0	530	50.9	15.6
Wildfire	12	7.1	26	2.5	2.2
Winter Storm	12	7.1	35	3.4	2.9

Table 1 Damage cost statistics from U.S. Billion-dollar disaster events (1980-2013) reflecting number of events, event frequency, CPI-adjusted loss (present year), percent of total losses and average event cost

2. Primary Insurance Loss Data and Assumptions

A number of U.S. insurance participation surveys have been performed over the last several decades for residential, automotive and commercial lines of insurance. The following paragraphs discuss the data from these surveys and how it informs our methodology to estimate the total, direct loss for a natural disaster event. One central adjustment is that insured loss payment data ($) are inflated by a factor representing the reciprocal of the insurance market participation rate for a specific type of insurance for each impacted state. Also, we test our disaster cost methodology calculations using a Monte Carlo analysis, which perturbs each data input value, to estimate 95%, 90% and 75% confidence intervals surrounding the overall loss estimate.

a. Residential Insurance:

Annual surveys on residential property insurance participation such as the Census American Housing Survey (1980-present), the Insurance Information Institute survey (2011-present), and All-Industry Research Advisory Council (1981) have indicated on average that > 90% of U.S. homeowners have multi-peril property insurance for their residence and contents (**Table 2**). This coverage includes cost reimbursement from damage due to wind, hail, lightning, snow and ice, among others, but does not include coverage for inland or coastal flood damage (discussed in section 2d).

Research also shows that residences are often underinsured. In 2013, 60% of homes were underinsured by an average of 17%; in 2012, 61% of homes were underinsured by an average of 18% (Marshall & Swift/Boeckh 2013). Scaling these statistics to represent the full housing stock implies that homeowners are *underinsured* by an average of ~10%. Therefore, in addition to the 10% who are also *uninsured*, we assume that 80%-90% of home losses are covered by insurance policies. The remaining 10%-20% represent uninsured and underinsured property assets.

It is also important to note that wind and water insurance deductibles average about 10% of all paid insurance claims (ISO Property Claims Service 2014, NFIP 2014) while insurance fraud payments represent about 10% of total property insurance payments (National Insurance Crime Bureau 2014, Insurance Information Institute 2014). Therefore, we assume that these two effects are offsetting (i.e., +10% for deductibles; -10% for fraud; with respect to total insurance payments) and viewed as tangential to our core analysis since fraud and deductible loss data are not consistently available.

Year	National Insured Housing Stock (%)	Year	National Insured Housing Stock (%)
1985	93.9	1999	93.6
1987	93.8	2001	93.9
1989	94.3	2003	93.2
1991	93.8	2005	93.7
1993	94.2	2007	94.4
1995	94.0	2009	94.6
1997	93.0	2011	94.1

Table 2 American Housing Survey percentage of U.S. households carrying residential property insurance

b. Automotive Insurance:

Annual U.S. uninsured motorist surveys (1989-2012) by the Insurance Research Council (IRC 2014) have also found a relatively stable percentage ranging from 80%-90% of automobiles insured (**Table 3**). Across the United States, the estimated percentage of insured motorists has increased in recent years (IRC 2014). In 2001, the average of insured motorists across all states was 85.8%, which increased to 87.8% in 2011 (IRC 2014). Given the variability of automobile insurance over time and space we assume that 80%-90% of automobiles are insured. The remaining 10%-20% represent uninsured and underinsured property assets.

Year	National Insured Motorists (%)	Year	National Insured Motorists (%)
1989	83.7	2001	85.8
1991	84.9	2003	85.1
1993	84.0	2005	85.4
1995	85.8	2007	86.2
1997	86.8	2009	86.2
1999	87.2	2011	87.8

Table 3 Percent of Uninsured Motorists by year averaged across the U.S.

c. Commercial Insurance:

Understanding damage to U.S. businesses is more complex. For example, a survey by the National Association of Insurance Commissioners (NAIC 2007) found that over 90% of the small businesses surveyed have property insurance. The percentage of companies with property insurance increases with the size of a company, which may reflect better risk management. However, many businesses lack business interruption insurance which is a large cost driver in the weeks and months following natural disaster events. For example, 32% of firms with annual revenue < $1 million had such coverage versus 48% of higher-revenue firms (**Table 4**). This is further validated by reports indicating that 20-40% of small businesses that close after a major natural disaster never reopen their business (IBHS 2007, Travelers 2014, III 2014). This can be due to a variety of reasons such as interruption of critical supplies and product distribution, power outages or other utility failures, loss of customer base and critical data, restricted or blocked access, employees unable to report to work, etc. Also, like homeowners, it was found that 75% of commercial buildings (i.e., physical property) are underinsured by an average of 40% (Marshall & Swift/Boeckh 2011, Travelers 2014). Marshall and Swift/Boekh (MSB) has data for 2,600 locations across the country and compares the information it has collected with actual reconstruction costs derived from its insurer clients' claims experience and adjusts as appropriate. Accounting for this variability and uncertainty surrounding different forms of commercial insurance, we estimate that 40-60% of natural disaster-induced business losses are covered by insurance.

Commercial Insurance Type	Total (%) of companies interviewed	# of Employees		Annual Revenue	
		1-19	**20-99**	**< $1 M**	**$1 M or more**
Property* / Liability	91	90	97	91	96
Commercial Auto	48	47	73	44	67
Business Interruption	35	33	58	32	48

Table 4 A study by NAIC (2007) found that commercial property, auto and business interruption insurance coverage varies by business size. *Research by Marshall & Swift/Boeckh (2011) found 75% of commercial buildings (i.e., building / contents) are underinsured by an average of 40% after examining data on businesses across 2,600 U.S. locations

In summary, we apply the 80-90% range to both residential and automotive PCS loss data and a 40-60% to commercial losses. We now take this research a step further to investigate the range of possible error by using a Monte Carlo analysis perturbing each of the data input values by +/-3% and +/-5% (i.e., reflecting the insurance survey data uncertainty on which assumptions are based). These values were chosen based on regulatory audits that routinely confirm the reliability and accuracy of ISO/PCS estimates, finding that final adjusted PCS estimates are within 5% accuracy (Kerney, 2010). Exploring different error levels allows us to better understand how the assumed insurance coverages affect the 95%, 90% and 75% confidence intervals surrounding our total loss estimate.

d. NFIP Flood Insurance:

We also have data on flood insurance participation, which factors into our disaster loss analysis. Residential and commercial flood insurance is most widely provided by FEMA's National Flood Insurance Program. Mortgage lenders require any residence within FEMA's Special Flood Hazard Areas (SFHAs) to purchase flood insurance. The SFHAs are commonly referenced as those within the 100-year flood plain boundaries. However, the enforcement and participation is not uniform and many at-risk properties do not have proper insurance coverage for flood or storm surge-related damage (**Table 5**). Annual polls on NFIP participation percentage by region show some consistency on a large scale across the Northeast, Midwest, and Western regions. Other studies have found the NFIP policy participation across the U.S. is higher (26%) for eligible parcels (PricewaterhouseCoopers 1999). However, these are still inadequately low participation rates leading to higher flood cost uncertainty.

	all U.S.	**Northeast**	**Midwest**	**South**	**West**
2008	17	20	17	17	15
2009	13	9	14	19	6
2010	10	9	6	14	9
2011	14	5	13	19	12
2012	13	14	6	21	6
2013	13	10	12	15	11
2014	13	11	7	20	8
2008-2014 average	13	11	11	18	10

Table 5 Insurance Information Institute annual survey on NFIP flood insurance participation percentage by region for all households

There is also a spatial bias in flood insurance policy coverage as NFIP participation is 16% in communities with 500 or fewer homes in the SFHA, 56% in communities with 501 to 5,000 homes in the SFHA, and 66% in communities with > 5,000 homes in the SFHA zone (Dixon et al. 2006). Also, the same research found that the chances of purchasing flood insurance are higher for SFHA communities subject to coastal flooding/storm surge (63%) compared to communities more at risk to riverine flooding (35%). One additional factor is that flood insurance coverage outside the high-risk flood areas (SFHAs) is very low (< than 10%). Yet, NFIP data show that 25% of all flood insurance claims come from the low-to-moderate-risk areas beyond the 100-year floodplain, which are largely uninsured losses (FEMA 2014). There are also NFIP coverage limits for residential ($250k structure, $100k contents) and commercial ($500k structure, $500k contents) properties (FEMA 2014). For these varied reasons, we have defined NFIP policy participation for the Monte Carlo uncertainty analysis as 10%-25% for inland states and 25%-50% for coastal states.

e. USDA Crop Insurance:

The USDA and associated private crop insurance programs represent over 2 million crop insurance policies across all states (USDA 2014). USDA data shows that on average across all states, 70% of eligible acres are insured and most producers select 70% of crop yield to be covered (USDA 2012). Therefore, we approximate the total crop loss by applying a factor to the crop insurance claims data; that is, 100% all possible crops/[(x% insured)*(50-75% yield coverage)] = multiplier value(s) for estimating total crop damage costs. The yield coverage is important as crop insurance is paid only after the crop loss has surpassed the selected yield coverage. For example, if a producer selected 70% coverage, the crop producer must first cover the first 30% of crop loss. This is effectively like a deductible, but paid to no one - just an absorbed cost.

In addition to crop losses, we also incorporate the total livestock feeding cost (i.e., corn and hay for cattle) when it exceeds the 5-year national average for feedstock (i.e., dollars/per ton). Drought can limit the availability of corn and hay feed stocks, which increases the cost forcing ranchers to sell off more cattle than they would during a non-drought year (e.g., increasing long-term meat production costs). Comparing the 5-year national vs. state feedstock costs against those during a severe drought-year offers a useful comparison.

f. Framing Uncertainty

In summary, we have set up our disaster cost uncertainty analysis using the following insurance participation ranges for the each line of insurance (**Table 6**). The next section discusses the output from Monte Carlo simulations to determine the 95%, 90% and 75% confidence intervals surrounding our total loss estimate for the following selected U.S. disaster events:

- the historic U.S. drought (2012),
- the Southeast tornado super-outbreak (late-April 2011),
- and Hurricane Ike (2008).

	Minimum	**Maximum**
Wind insurance (PCS – Residential)	80%	90%
Wind insurance (PCS – Automotive)	80%	90%
Wind insurance (PCS - Commercial)	40%	60%
Flood insurance (FEMA) For coastal states	25%	50%
Flood insurance (FEMA) For inland states	10%	25%
Crop insurance (USDA) Multi-peril (drought, flood, etc.)	50%	75%

Table 6 Insurance participation rate ranges used in the Monte Carlo simulation.

3. Method for Estimating Uncertainty Surrounding Natural Disaster Loss Estimates

A Monte Carlo approach is employed to assess the uncertainty of disaster loss estimates. For each of the three events detailed below, the parameters of the equations as outlined in Smith & Katz (2013) were perturbed to produce a distribution of loss estimates. There are two general categories of input parameters: 1) insurance participation rates, and 2) loss values. The defined possible ranges for insurance participation rates were justified in Section 2. We assumed either a +/- 3 or 5% error for the loss values. For final ISO/PCS insurance loss results, a 3% bound of uncertainty should be adequate. Regulatory audits routinely confirm the reliability and accuracy of PCS estimates. Historically, after such regulatory data audits, the final adjusted estimate has differed by at most 5% (Booz Allen Hamilton personal communication 2013). We also assumed that the parameters were either uniformly or normally distributed within the ranges. Therefore, there are four cases examined for each of the following events:

+/- 3% error on loss values with uniformly distributed parameters,
+/- 5% error on loss values with uniformly distributed parameters,
+/- 3% error on loss value with normally distributed parameters, and
+/- 5% error on loss value with normally distributed parameters.

10000 simulations were run for each case by random draws within the defined ranges with the defined distributions. Confidence intervals were calculated by sorting the 10000 loss estimates in ascending order, then using a percentile method to define the confidence region. For example, to construct the 95% confidence region, the 250th and 9750th predictions were selected as the lower and upper bounds, respectively.

a. 2012 U.S. drought

Our first example is the 2012 drought, which resulted in the most extensive drought impacts to affect the U.S. in decades (NCDC 2014). Moderate to extreme drought conditions affected more than half the country for the majority of 2012. The most costly drought impacts occurred across the central agriculture states resulting in widespread harvest failure for corn, sorghum and soybean crops, among others. Using the USDA crop insurance and feed cost data with the disaster cost methodology described in (Smith and Katz 2013), the 2012 U.S. drought cost to agriculture was estimated to be $30.0 billion (NCDC 2014).

To verify the uncertainty surrounding this estimate, this research examines 4 different cases of Monte Carlo simulation for this event. This was performed using a USDA 'percent of eligible acres insured,' as a separate crop value metric from the USDA 'percentage of insurable crop value' used to calculate the cost of the 2012 U.S. drought, as described in section 2. In all cases, the following loss values used are summarized in **Table 7** and the range of crop insurance participation rates ($p_{crop\_yield\_cov}$) are referenced in **Table 6**.

The final loss estimate was calculated by:

$$TOTAL = \sum_{i=\,all\ states} [m_i v_i\,] + v_{incFeedCost}$$

where

$$m_i = \frac{100}{p_{acres\_insured} * \ p_{crop_{yield_{cov}}}}$$

State	Insurance payout ($ million)	Percent eligible acres insured
Alabama	19.272608	61
Arkansas	17.157674	67
California	11.133870	34
Colorado	121.977411	70
Delaware	12.641902	81
Iowa	1856.441799	91
Idaho	4.180436	53
Illinois	**2861.989110**	**79**
Indiana	1027.963734	72
Kansas	1011.764735	89
Kentucky	359.356293	59
Maryland	121.572572	72
Michigan	131.354503	61
Minnesota	163.322190	90
Missouri	1024.195287	65
Mississippi	17.484280	83
Montana	51.007988	80
North Dakota	**111.085759**	**96**
Nebraska	1204.855900	85
New Mexico	23.019718	53
New York	**9.711831**	**27**
Ohio	315.336961	68
Oklahoma	94.791212	70
Pennsylvania	11.653171	30
South Dakota	963.773831	94
Tennessee	105.039149	58
Texas	780.123224	76
Virginia	31.021328	48
Wisconsin	363.021359	57
Wyoming	6.106170	29
OTHER		
Increased Feed Cost	3614.419032	

Table 7 USDA crop indemnity (loss) payout information for each state due to the combined effects of drought and heat in 2012. The percent of acres in each state that have USDA crop insurance are also provided. For the Monte Carlo simulation, values in the above table were considered to be within the associated ranges of +/-3% or +/-5%. State of particular interest have been highlighted in boldface: Illinois (largest state payout), North Dakota (highest percent of eligible acres insured), and New York (lowest percent of eligible acres insured).

The results of the Monte Carlo analysis are provided (**Table 8**). We see that the estimated $30 billion total, direct cost of the 2012 U.S. drought (NCDC 2014) is reasonably close to the mean and median of the Monte Carlo simulation. **Figures 1a, 1b, 2a** and **2b** present the histograms of the 10000 estimates for each case, along with confidence interval bounds.

A histograms of multiplier (m_i) values from a selection of states (i.e., Illinois, New York and North Dakota) affected by the 2012 U.S. drought is shown in **Figure 3**. Here we see the range of possible multiplier values applied to the state insurance payout amount. Given the inverse relationship of the multiplier to the percent of acres insured, we see that states with smaller percentages of acres insured (i.e. New York) will have larger associated multiplier values.

	3% Normal	**3% Uniform**	**5% Normal**	**5% Uniform**
Minimum	27326	27114	27623	27216
Maximum	34661	34230	35402	34903
Mean	30416	30378	30507	30620
Median	30384	30349	30466	30577
75% CI	29398, 31467	29174, 31611	29455, 31591	29383, 31883
90% CI	28986, 31968	28712, 32130	29028, 32102	28922, 32464
95% CI	28728, 32303	28461, 32467	28760, 32459	28648, 32799

Table 8. Results (in $ million) of the four cases analyzing the total cost of the 2012 U.S. drought on crops and livestock (in original year dollars).

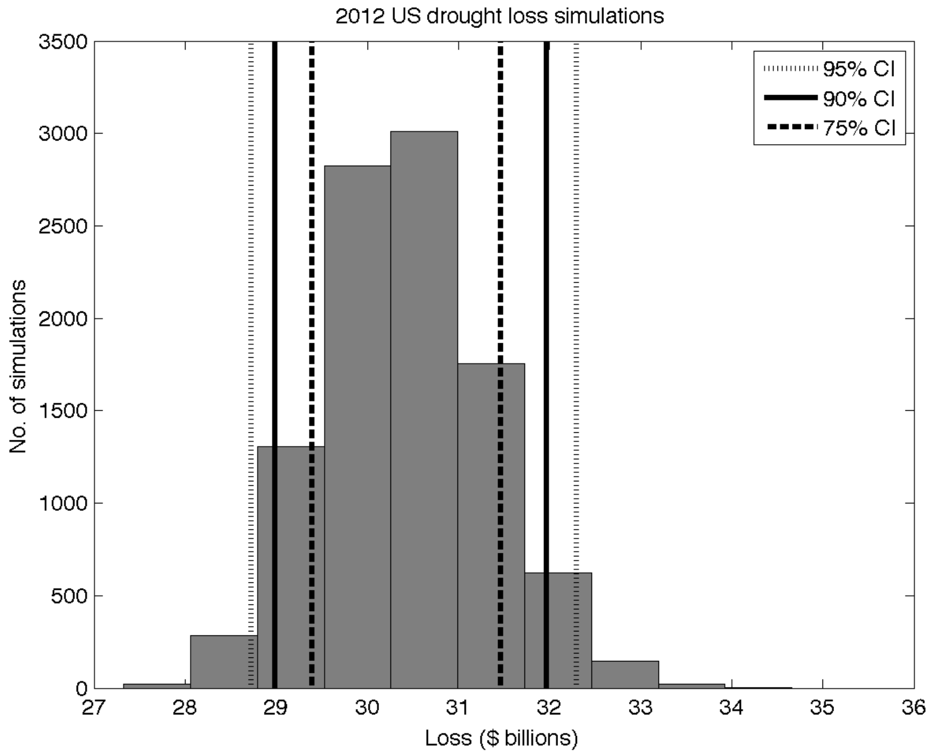

Fig. 1a Case 1 results: 3% perturbation on values, parameters normally distributed

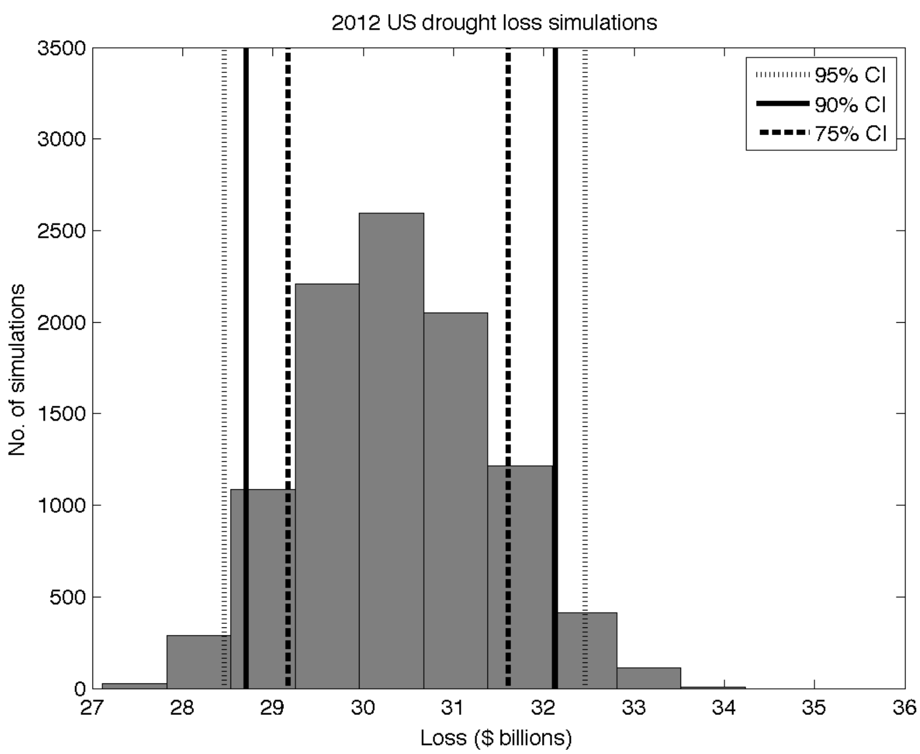

Fig. 1b Case 2 results: 3% perturbation on values, parameters uniformly distributed

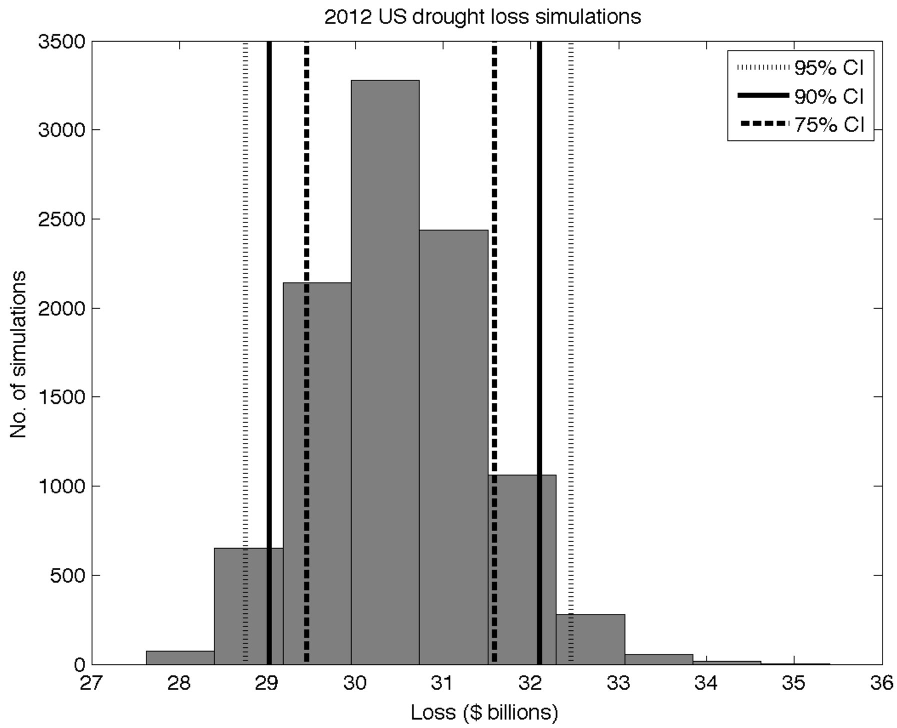

Fig. 2a Case 3 results: 5% perturbation on values, parameters normally distributed

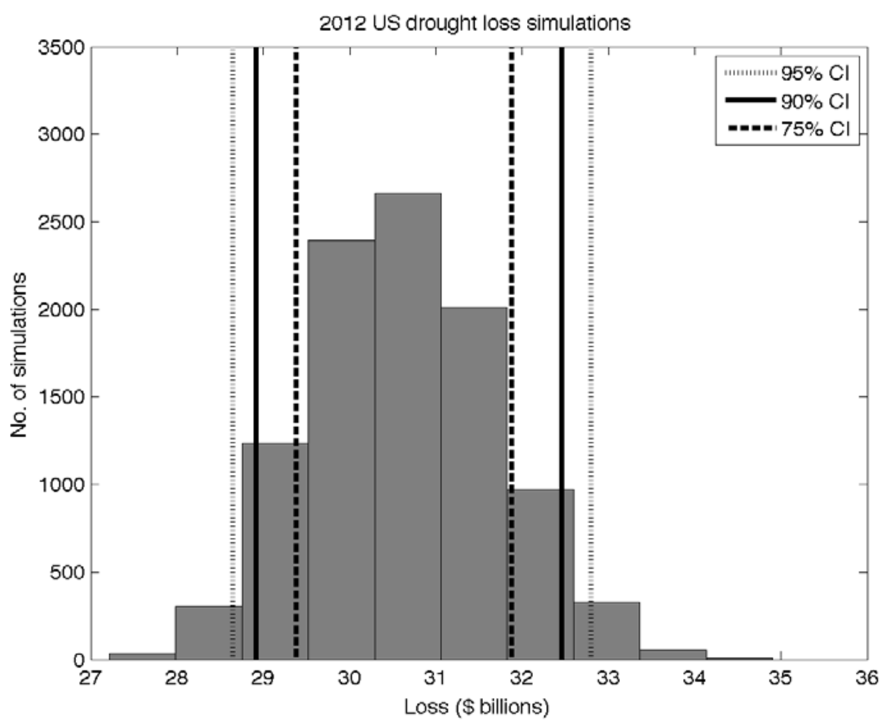

Fig. 2b Case 4 results: 5% perturbation on values, parameters uniformly distributed

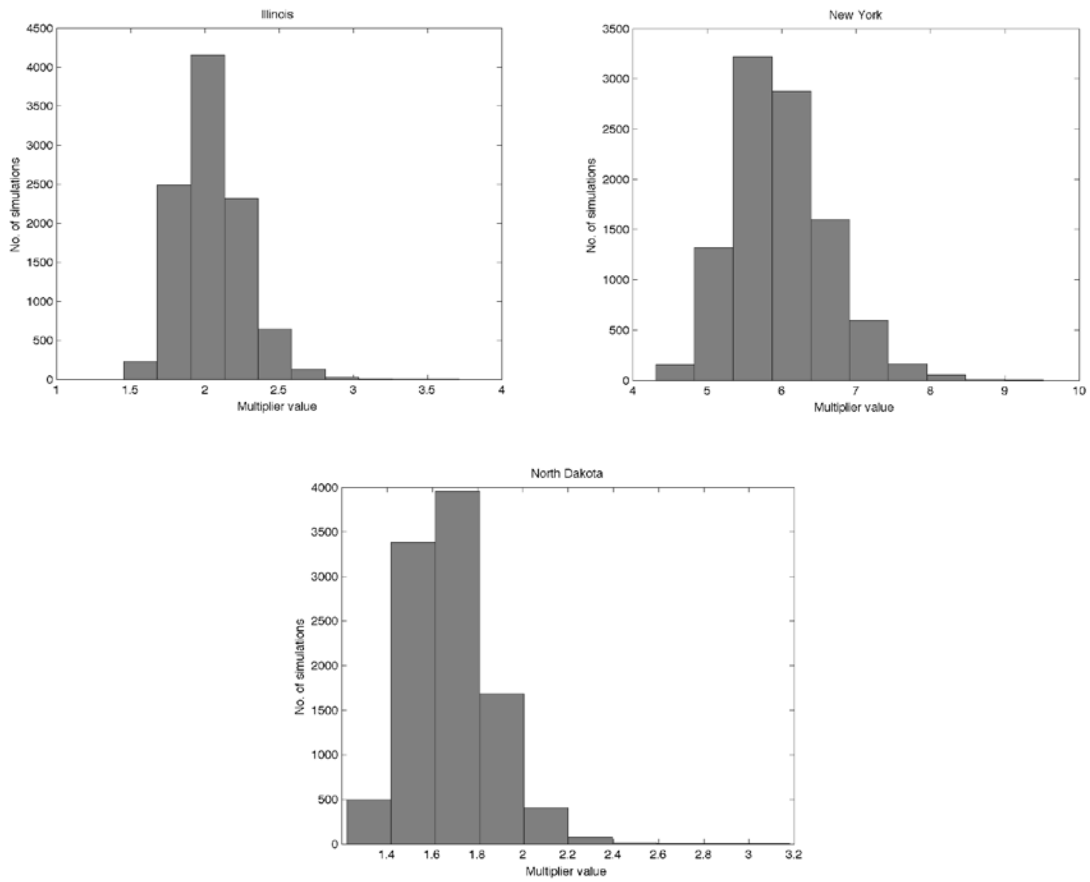

Fig. 3 Histograms of multiplier values (m_i) for several states affected by the 2012 U.S. drought disaster. All of these are from Case 3 (+/- 5% error, normally distributed parameters). Illinois had the largest insurance payout (top left). New York had the smallest percent of eligible acres insured (top right). North Dakota had the largest percent of eligible acres insured (bottom).

b. **April 25-28, 2011 Tornado Outbreak**

Our second example examines a historic tornado outbreak across numerous central and southern states in late-April, 2011. Several major metropolitan areas were directly impacted by strong tornadoes including Tuscaloosa, Birmingham, and Huntsville in Alabama and Chattanooga, Tennessee, causing the estimated damage costs to soar. The total, direct cost for this event was estimated to be approximately $9.8 billion (NCDC 2014). To verify the uncertainty surrounding this estimate, this research examines 4 different cases of Monte Carlo simulation for this event. In all cases, the following loss values used are summarized in **Table 9** indicating the data values for each state and insurance claim type used in the total, direct loss calculation.

State	**PCS Commercial ($ million)**	**PCS Residential ($ million)**	**PCS Automotive ($ million)**	**FEMA PDD ($ million)**
Alabama	1000.0	1500.0	150.0	396.6
Arkansas	45.0	175.0	53.0	-
Georgia	135.0	240.0	20.0	34.9
Illinois	7.0	45.0	12.0	-
Kentucky	31.0	73.5	7.5	48.9
Louisiana	16.0	43.0	11.0	-
Missouri	125.0	125.0	30.0	-
Mississippi	73.0	85.0	11.0	44.5
Ohio	30.0	66.0	2.0	-
Oklahoma	10.0	39.0	16.0	-
Tennessee	410.0	980.0	395.0	76.8
Texas	135.0	320.0	110.0	-
Virginia	19.0	38.0	17.0	-

Table 9 Loss values from the April 25-28, 2011 Tornado Outbreak. For the Monte Carlo simulation, values in the above table were considered to be within the associated ranges of +/-3% or +/-5%.

The final loss estimate was calculated by:

$$TOTAL\ LOSS = \sum_{i=\ all\ states} \left[m_{i,PCS_{comm}} v_{j,PCS_{comm}} + m_{i,PCS_{res}} v_{j,PCS_{res}} + m_{i,PCS_{auto}} v_{j,PCS_{auto}} + v_{i,FEMA_{PDD}} * \left(v_{i,FEMA_{PDD}} > m_{i,PCS\_total} v_{i,PCS_{total}} \right) \right]$$

where

$m_{i,PCS_{comm}}$ is the multiplier for commercial PCS

$m_{i,PCS_{res}}$ is the multiplier for residential PCS

$m_{i,PCS_{auto}}$ is the multiplier for automotive PCS

and these multipliers are defined as:

$$\text{Multiplier} = \frac{100}{insurance\ participation\ rate}.$$

For the comparison part of the equation we define:

$$v_{i,PCS\_total} = v_{i,PCS\_comm} + v_{i,PCS\_res} + v_{i,PCS\_auto} \text{ (NOTE: no multipliers involved)}$$

$$m_{i,PCS_{total}} = \frac{m_{i,PCS_{comm}} v_{j,PCS_{comm}} + m_{i,PCS_{res}} v_{j,PCS_{res}} + m_{i,PCS_{auto}} v_{j,PCS_{auto}}}{v_{i,PCS\_total}} - 1$$

The results of the Monte Carlo analysis are provided (**Table 10**). **Table 6** contains the insurance participation rates. We see that the estimated $9.8 billion total, direct cost of the April 25-28 tornado outbreak (NCDC 2014) is reasonably close to the mean and median of the Monte Carlo simulation. **Figures 4a, 4b, 5a** and **5b** present the histograms of the 10000 estimates for each case, along with confidence interval bounds.

	3% Normal	**3% Uniform**	**5% Normal**	**5% Uniform**
Minimum	8756.4	8759.0	8742.5	8713.5
Maximum	10833	10429	10685	10426
Mean	9519.2	9532.1	9523.7	9529.6
Median	9502.4	9513.2	9505.1	9511.9
75% CI	9246.1, 9801.1	9200.3, 9884.7	9245.1, 9817.8	9192.1, 9891.6
90% CI	9148.9, 9945.3	9097.7, 10016	9130.3, 9964.6	9079.4, 10026
95% CI	9090.5, 10043	9039.5, 10085	9066.5, 10071	9023.2, 10107

Table 10 Results (in $ million) of the four cases analyzing the April 2011 Tornado Outbreak total cost.

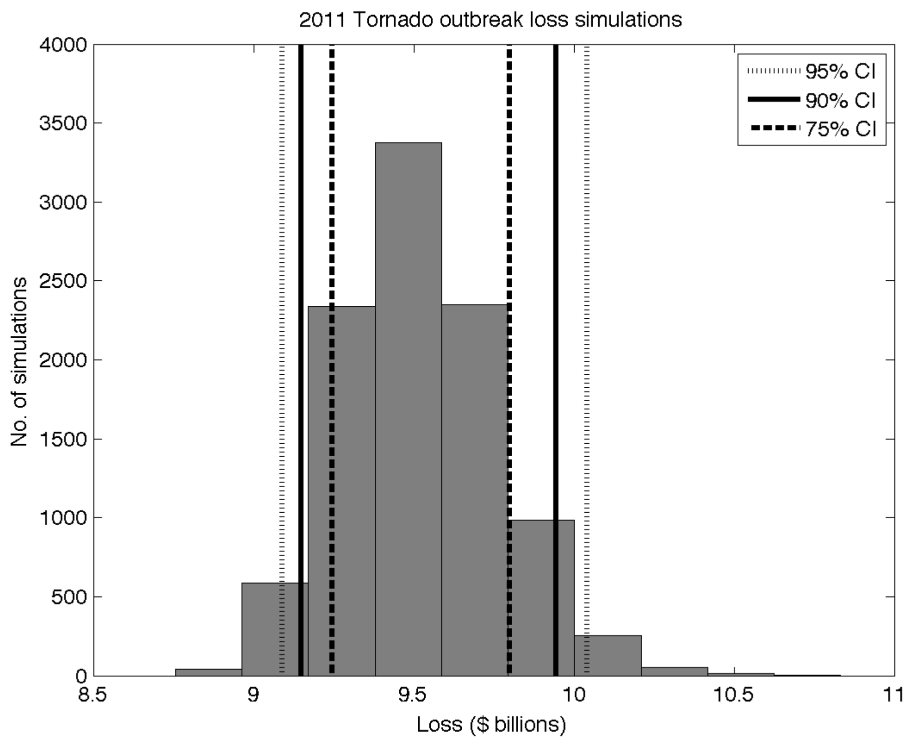

Fig. 4a Case 1 results: 3% perturbation on values, parameters normally distributed

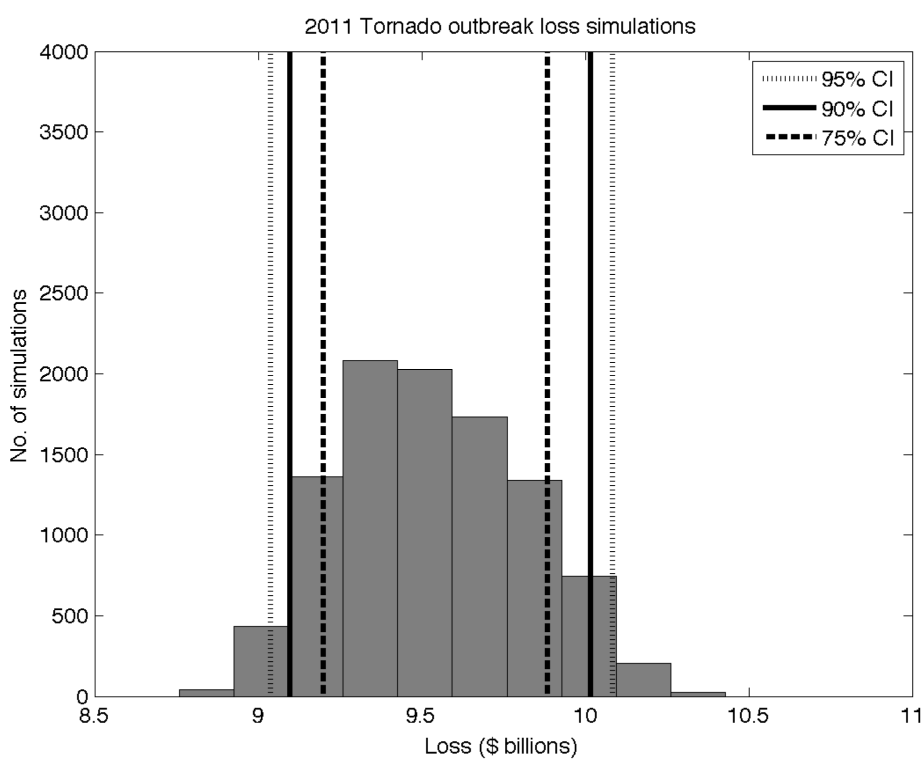

Fig. 4b Case 2 results: 3% perturbation on values, parameters uniformly distributed

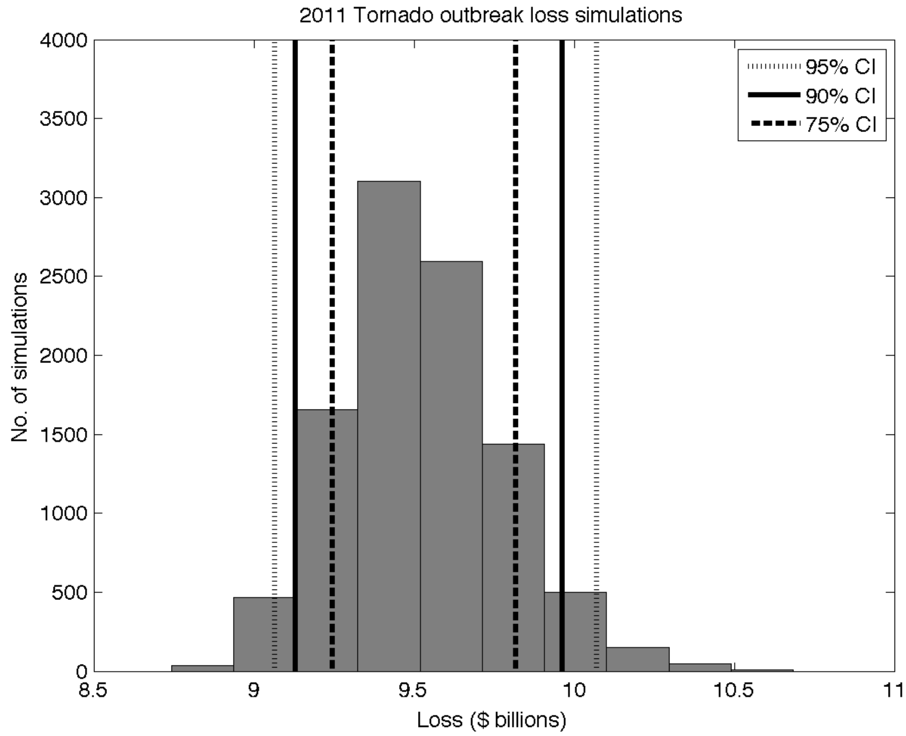

Fig. 5a Case 3 results: 5% perturbation on values, parameters normally distributed

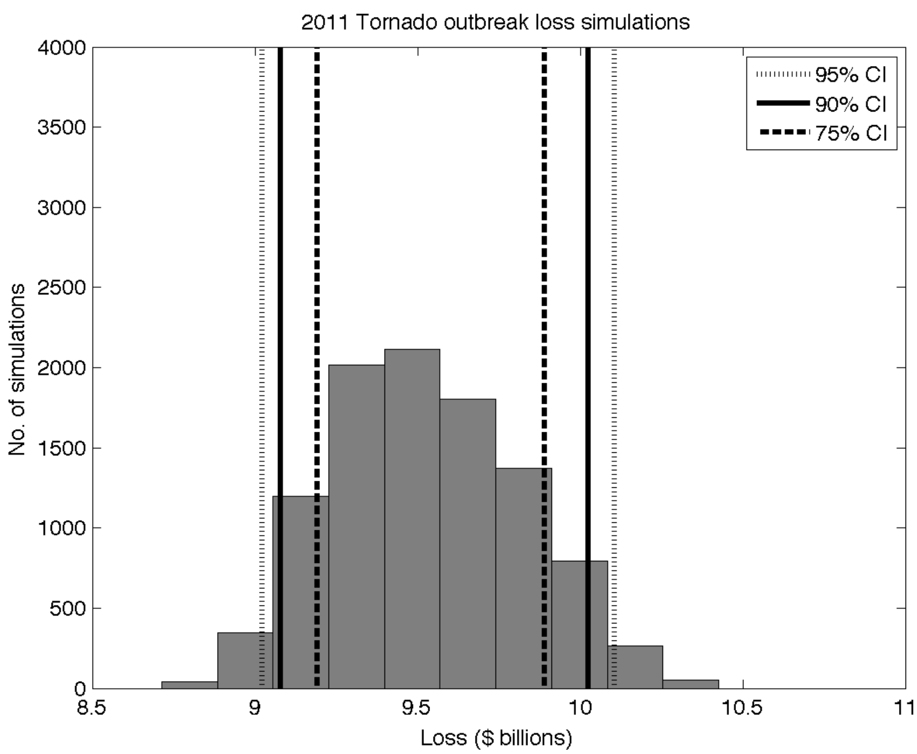

Fig. 5b Case 4 results: 5% perturbation on values, parameters uniformly distributed

c. September 2008 - Hurricane Ike

In September 2008, Hurricane Ike caused extensive storm-surge and wind damage in Texas. There was also caused considerable wind and flood damage across many other coastal and inland states (i.e., Louisiana, Arkansas, Tennessee, Illinois, Indiana, Kentucky, Missouri, Ohio and Pennsylvania). Severe gasoline shortages occurred in the southeast U.S. due to damaged oil platforms, storage tanks, pipelines and off-line refineries. After examining the loss data sources using our tropical cyclone cost methodology it was determined that the total, direct cost of Ike was approximately $30.0 billion (NCDC 2014). To verify the uncertainty surrounding this estimate, this research examines 4 different cases of Monte Carlo simulation for this event. In all cases, the following loss values used are summarized in **Table 11**. **Table 6** contains the insurance participation rates. Note that we consider coastal and inland states separately when including a multiplier to the FEMA NFIP loss values. Coastal states for this example are: Alabama, Louisiana and Texas. The inland states are: Illinois, Indiana, and Missouri.

	PCS Comm. ($ million)	**PCS Residential ($ million)**	**PCS Auto. ($ million)**	**FEMA PDD ($ million)**	**FEMA NFIP ($ million)**
Alabama	-	-	-	13.1	1.7
Arkansas	12.5	35.0	8.5	2.5	-
Illinois	50.0	150.0	40.0	108.0	54.3
Indiana	80.0	230.0	20.0	93.0	32.3
Kentucky	110.0	405.0	18.0	18.9	-
Louisiana	50.0	50.0	35.0	263.0	321.0
Missouri	16.0	50.0	10.0	-	42.5
Ohio	255.0	960.0	40.0	39.6	-
Penn.	8.0	63.0	4.0	-	-
Texas	4000.0	5500.0	300.0	2464.0	2185.9
OTHER					
Oil platform damage	3000.0				
Agriculture & Forestry	825.0				

Table 11 Loss values from the Hurricane Ike disaster. For the Monte Carlo simulation, values in the above table were considered to be within the associated ranges of +/-3% or +/-5%.

The final loss estimate was calculated by:

$$TOTAL\ LOSS = \sum_{i=\ all\ states} \left[m_{i,PCS_{comm}} v_{j,PCS_{comm}} + m_{i,PCS_{res}} v_{j,PCS_{res}} + m_{i,PCS_{auto}} v_{j,PCS_{auto}} + m_{i,FEMA_{NFIP}} v_{i,FEMA_{NFIP}} + v_{i,FEMA_{PDD}} * \left(v_{i,FEMA_{PDD}} > v_{i,PCS_{total}}\right)\right] + v_{state} + v_{USDA}$$

where

$v_{i,PCS\_total} = v_{i,PCS\_comm} + v_{i,PCS\_res} + v_{i,PCS\_auto}$ (NOTE: no multipliers involved)

$m_{i,PCS_{comm}}$ is the multiplier for commercial PCS

$m_{i,PCS_{res}}$ is the multiplier for residential PCS

$m_{i,PCS_{auto}}$ is the multiplier for automotive PCS

$m_{i,FEMA_{NFIP}}$ is the multiplier for FEMA NFIP

and

$$\text{Multiplier} = \frac{100}{insurance\ participation\ rate}$$

The results of the Monte Carlo analysis are provided (**Table 12**). We see that the estimated $30 billion total, direct cost of Hurricane Ike is remarkably close to the mean and median of the Monte Carlo simulation. **Figures 6a, 6b, 7a** and **7b** present the histograms of the 10000 estimates for each case, along with confidence interval bounds.

	3% Normal	**3% Uniform**	**5% Normal**	**5% Uniform**
Minimum	26539	26669	26308	26518
Maximum	40922	35468	39065	35571
Mean	30356	30451	30334	30445
Median	30233	30382	30191	30355
75% CI	28808, 31974	28592, 32368	28772, 31995	28518, 32435
90% CI	28311, 32903	28003, 33205	28232, 32883	27963, 33327
95% CI	27998, 33661	27720, 33668	27886, 33508	27634, 33802

Table 12 Results (in $ million) of the four cases analyzing the total cost of Hurricane Ike.

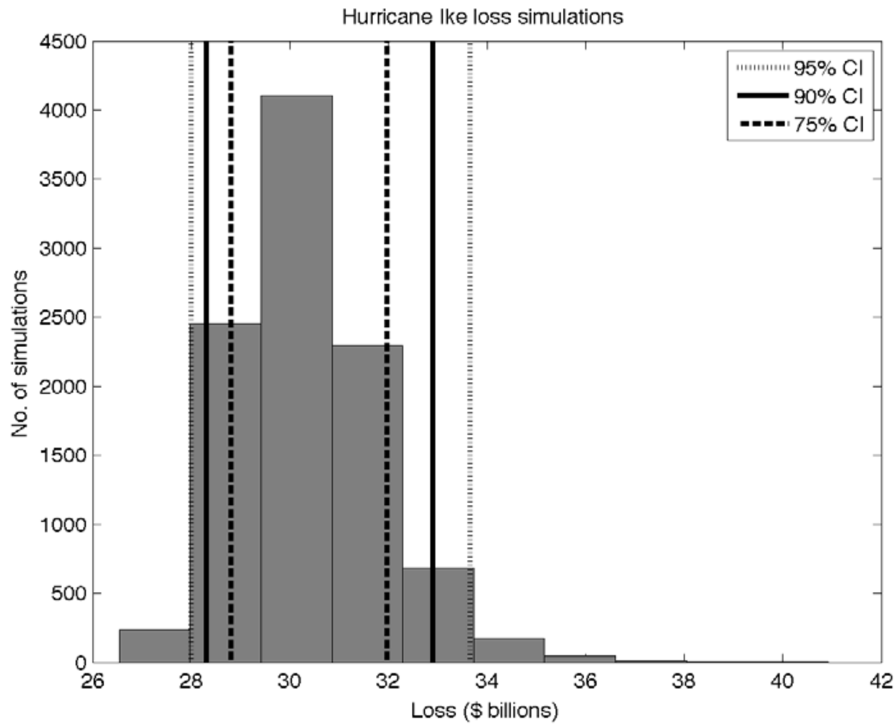

Fig. 6a Case 1 results: 3% perturbation on values, parameters normally distributed

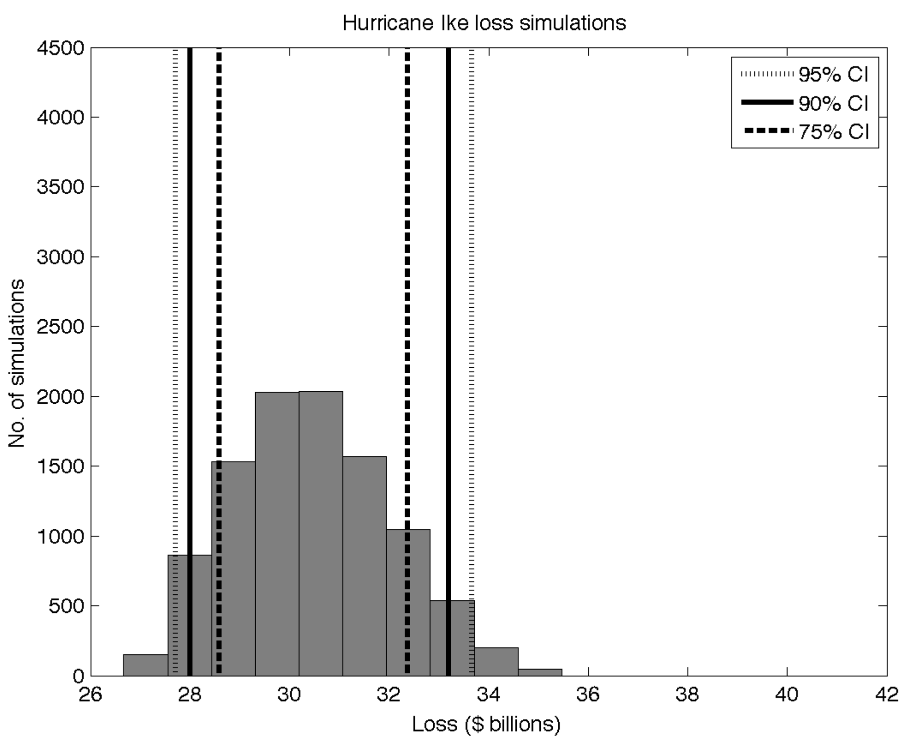

Fig. 6b Case 2 results: 3% perturbation on values, parameters uniformly distributed

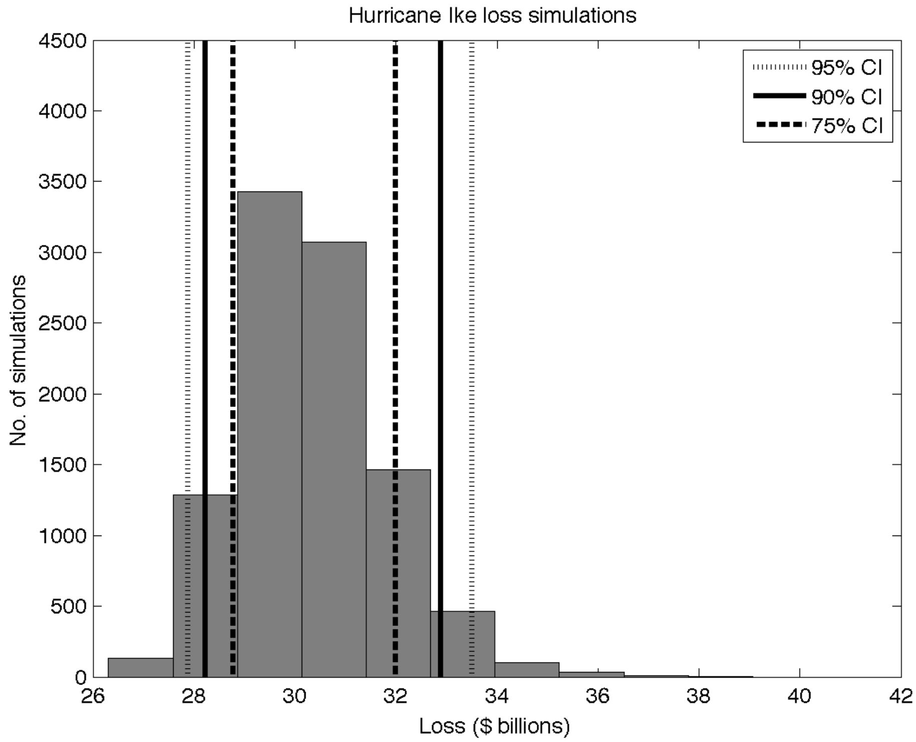

Fig. 7a Case 3 results: 5% perturbation on values, parameters normally distributed

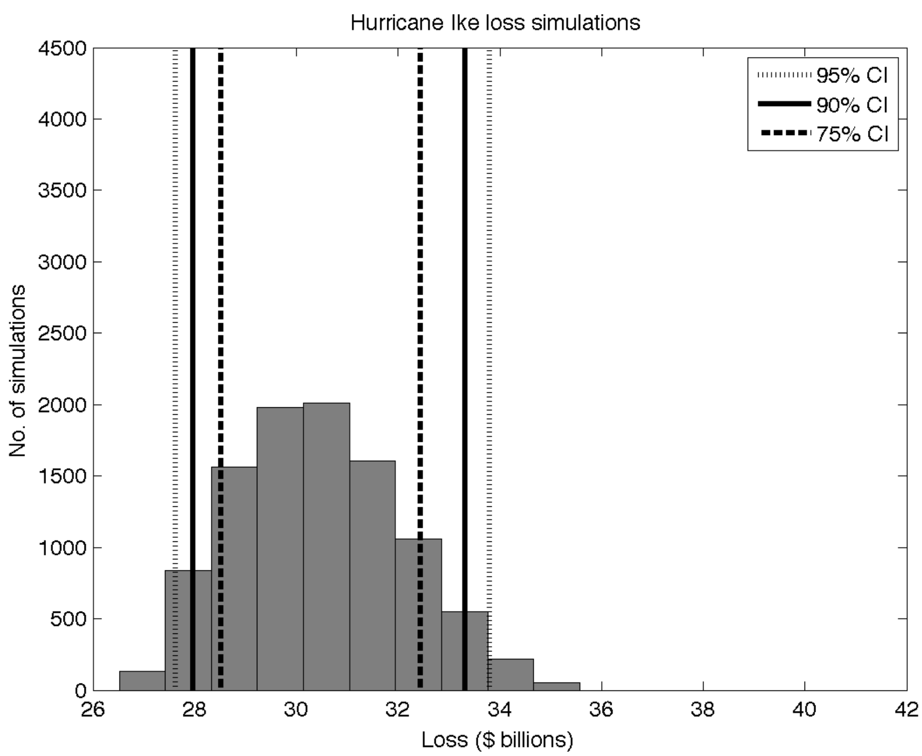

Fig. 7b Case 4 results: 5% perturbation on values, parameters uniformly distributed

4. Effects of Sensitivity Analysis on Overall Cost Estimate

For each of the total, direct loss estimates for natural disaster events there are a number of input parameters, each with an associated degree of uncertainty. We wanted to explore how the estimates respond to perturbations in the input parameters, so we performed a sensitivity analysis for a single case study. The following analysis is one-dimensional, that is, perturbing only one parameter at a time. We began with a base set of parameters θ, taken to be the mean of the ranges defined in the examples of Section 3. The associated loss estimate f(θ) was calculated based on this set of parameters. Then we applied a 1% perturbation to each parameter forming a new set of parameters θ_i, for i=1, …n where n is the number of input parameters. Then the associated loss estimates $f(\theta_i)$ were calculated. Finally, in order to compare sensitivities fairly, they were normalized by the magnitude of the values. The normalized sensitivity of f to the ith parameter, s_i, can be written

$$s_i = \frac{df(\theta)}{d\theta} = \left(\frac{f(\theta_i) - f(\theta)}{\theta_i - \theta}\right) * \left(\frac{\theta}{f(\theta)}\right)$$

Taking the Hurricane Ike disaster as an example, we explored the sensitivity of the total loss estimate to each of the input parameters. In all there are 76 inputs for this calculation. The results are presented in **Figure 8**. We see that the most sensitive parameters for the Hurricane Ike estimate are the PCS commercial insured loss value and associated multiplier for Texas. We may interpret this to mean that a change in the PCS commercial value or multiplier for Texas would impact the total loss estimate of Hurricane Ike more than changing any other parameter. Therefore, if the goal is to reduce the uncertainty of the total loss estimate for this Hurricane Ike example, the best way forward is to reduce the uncertainty in the PCS commercial value and the PCS commercial insurance participation rate for Texas, and then continue with subsequent parameters in order of descending sensitivity.

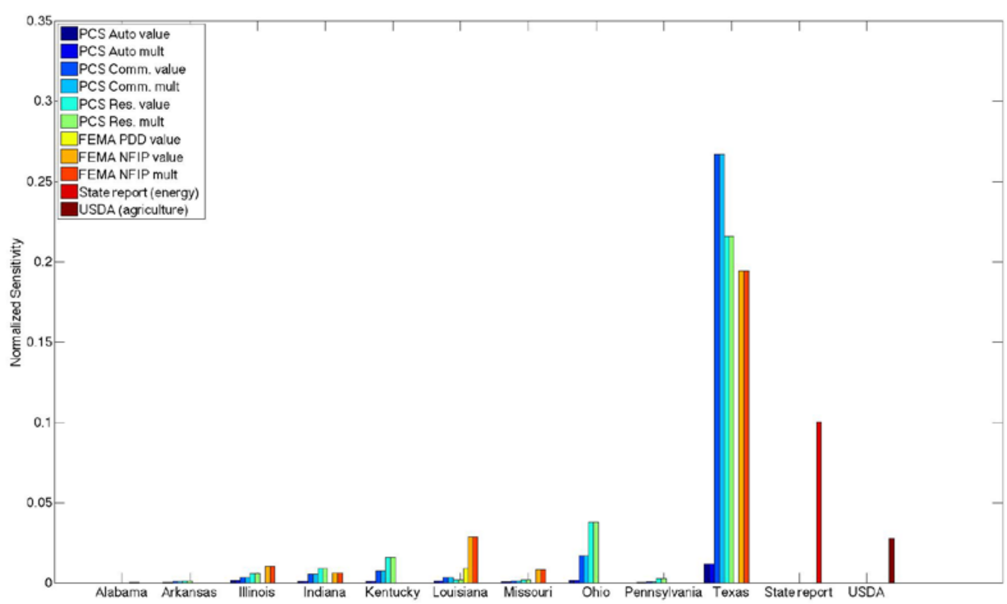

Fig. 8 Normalized sensitivity analysis of damage totals caused by Hurricane Ike by state and loss data category.

5. Discussion and Conclusion

The Monte Carlo simulations for all three of the natural disaster case studies provide additional confidence in our total, direct loss estimates (NCDC 2014) for these events since the estimates are within the confidence limits and close to the mean and median of the Monte Carlo simulations for each disaster example. The reason that some differences are present is because the total, direct loss estimates for each event, as reported in NCDC (2014), use a slightly different approach to loss calculation. Whereas in NCDC (2014) the PCS loss component values are grouped together, in this analysis we treat the Residential, Commercial, and Automotive category losses separately. Here we are leveraging the information gathered through the survey review, as described in Section 2, to incorporate more granular insurance multiplier values than those used previously as well. In this analysis we defined ranges for insurance participation and subsequently used these to calculate the associated multipliers.

The confidence intervals are of value because they provide greater clarity to the quality of the assessment. For each of the three case studies, we examined the impact of two main assumptions, the error present in the loss values and the distribution of the possible values. For the April 25-28, 2011 tornado outbreak and Hurricane Ike, the impact of assuming 3% or 5% error on loss values was negligible according to hypothesis testing to determine if the samples were from the same distribution (using Kolmogorov-Smirnov, Wilcoxon rank-sum, and Wilcoxon signed-rank tests). However, these same hypothesis tests indicate that the choice of a normal or a uniform distribution of loss values was more important. This is especially noticeable when comparing histograms, where the simulations with the normal assumption tend to have longer upper tails than the simulations with the uniform assumption. Therefore, in the interest of being more conservative in the choice of confidence bounds, we recommend the confidence intervals as derived from assuming 5% error on uniformly distributed loss values.

The 2012 U.S. drought example had different results from the hypothesis testing. Here, the impact of both assumptions was important. The cases assuming uniformly distributed values resulted in wider, and hence more conservative, confidence regions. Increasing the assumed error on loss values from 3% to 5% also caused the confidence regions to enlarge, and additionally caused a positive shift. Although the confidence regions from the four cases are not perfectly nested, all things considered assuming 5% error on uniformly distributed loss values provides the most conservative confidence region estimate.

We also performed a sensitivity analysis examining how the separate loss variables contribute to the overall loss total for a specific case study. It is not surprising that when examining the Hurricane Ike disaster we found that the Texas insurance cost variables had the most sensitivity, as Texas experienced the largest loss values for all data categories; residential, automotive, commercial, and NFIP flood-related losses. The offshore energy losses were also quite sensitive to the overall cost estimate. The total loss estimate for Hurricane Ike used 76 input parameters, each of which has some uncertainty which contributes to the uncertainty in the total loss estimate. The intent of the sensitivity analysis described in Section 4 was to isolate the most important parameters to focus on reducing the uncertainty, which will in turn have the greatest impact in reducing the uncertainty in the total loss estimate.

Although we explore Monte Carlo simulations for just several disaster examples, we seek to apply this methodology to all of the U.S. Billion-dollar weather and climate event loss estimates (NCDC 2014) to provide better context regarding disaster cost uncertainty. This research is a next step to enhance the value and usability of estimated disaster costs given data limitations and inherent complexities.

Acknowledgments

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