Nat Hazards
DOI 10.1007/s11069-013-0566-5

ORIGINAL PAPER

US billion-dollar weather and climate disasters: data sources, trends, accuracy and biases

Adam B. Smith · Richard W. Katz

Received: 23 October 2012 / Accepted: 17 January 2013

Abstract This paper focuses on the US Billion-dollar Weather/Climate Disaster report by the National Oceanic and Atmospheric Administration's National Climatic Data Center. The current methodology for the production of this loss dataset is described, highlighting its strengths and limitations including sources of uncertainty and bias. The Insurance Services Office/Property Claims Service, the US Federal Emergency Management Agency's National Flood Insurance Program and the US Department of Agriculture's crop insurance program are key sources of quantified disaster loss data, among others. The methodology uses a factor approach to convert from insured losses to total direct losses, one potential limitation. An increasing trend in annual aggregate losses is shown to be primarily attributable to a statistically significant increasing trend of about 5 % per year in the frequency of billion-dollar disasters. So the question arises of how such trend estimates are affected by uncertainties and biases in the billion-dollar disaster data. The net effect of all biases appears to be an underestimation of average loss. In particular, it is shown that the factor approach can result in a considerable underestimation of average loss of roughly 10–15 %. Because this bias is systematic, any trends in losses from tropical cyclones appear to be robust to variations in insurance participation rates. Any attribution of the marked increasing trends in crop losses is complicated by a major expansion of the federally subsidized crop insurance program, as a consequence encompassing more marginal land. Recommendations concerning how the current methodology can be improved to increase the quality of the billion-dollar disaster dataset include refining the factor approach to more realistically take into account spatial and temporal variations in insurance participation rates.

Keywords Natural disasters · Losses · Statistics of extreme events · Data sources

A. B. Smith (✉)
NOAA National Climatic Data Center, 151 Patton Avenue, Asheville, NC 28801, USA
e-mail: Adam.Smith@noaa.gov

R. W. Katz
National Center for Atmospheric Research, Boulder, CO, USA

Published online: 03 February 2013

1 Introduction

The US Billion-dollar Weather/Climate Disaster report by the National Oceanic and Atmospheric Administrations's National Climatic Data Center provides readers with an aggregated loss perspective for major weather and climate events since 1980 (NCDC 2012). This report quantifies the loss from numerous weather and climate disasters including: tropical cyclones, floods, droughts/heat waves, severe local storms (e.g., tornado, hail, straight-line wind damage), wildfires, crop freeze events and winter storms. 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 losses include: physical damage to residential, commercial and government/municipal buildings, material assets within a building, time element losses (i.e., time–cost for businesses and hotel-costs for loss of living quarters), vehicles, public and private infrastructure, and agricultural assets (e.g., buildings, machinery, livestock). Our disaster 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 whose losses exceed the billion-dollar threshold, in US $ for the year 2011 adjusted for inflation using the Consumer Price Index (CPI), are included in this dataset (Fig. 1). While this threshold is somewhat arbitrary, these billion-dollar events account for roughly 80 % of the total ($880B out of $1,100B) US losses for all combined severe weather and climate events (Munich Re 2012; NCDC 2012). This adjustment does allow some disaster events that have nominal losses less than $1 billion to be counted, but these events reflect only 19 of 133 total events. The distribution of the damage and frequency of these disasters across the 1980–2011 period of record is

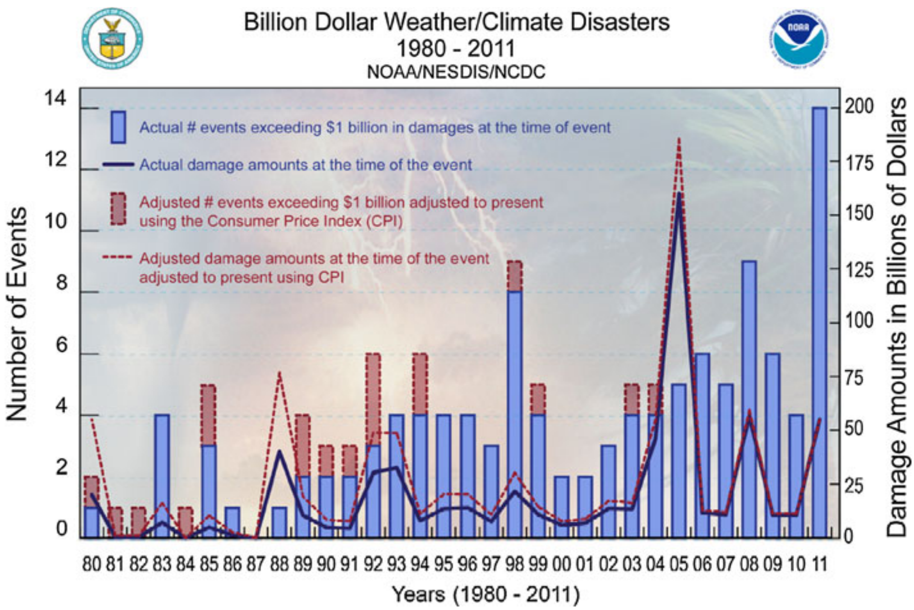


Fig. 1 US billion-dollar weather and climate disaster time series from 1980–2011 indicates the number of annual events exceeding $1 billion in direct damages, at the time of the event and also adjusted to 2011 dollars using the consumer price index (CPI)

Table 1 Damage, percent damage, frequency and percent frequency by disaster type across the 1980–2011 period for all billion-dollar events (adjusted for inflation to 2011 dollars)

	Number of events	Adjusted damages ($ Billions)	Percent damage	Percent frequency
Tropical cyclones	31	417.9	47.4	23.3
Droughts/heatwaves	16	210.1	23.8	12.0
Severe local storms	43	94.6	10.7	32.3
Non-tropical floods	16	85.1	9.7	12.0
Winter storms	10	29.3	3.3	7.5
Wildfires	11	22.2	2.5	8.3
Freezes	6	20.5	2.3	4.5
Total	133	881.2	100.0	100.0

dominated by tropical cyclone losses (Table 1), but the frequency and loss totals from severe local storms increased the most over the last several years.

First, the current methodology for the production of the US billion-dollar disaster loss dataset is described. The goal is to highlight strengths and limitations of this dataset, identifying potential sources of uncertainty and bias. Because most of the data sources provide only insured losses, a "factor approach" (based on approximate average insurance participate rates) is used for conversion into the corresponding total losses. A number of studies have concluded that population growth, increased value of property at risk and demographic shifts are major factors behind the increasing losses from weather and climate disasters (Pielke et al. 2008; Downton and Pielke 2005; Brooks and Doswell 2001). Nevertheless, the billion-dollar disaster dataset is only adjusted for inflation.

Figure 1 suggests apparent increasing trends in both the annual frequency of billion-dollar events and in the annual aggregate loss from these events. So, another goal of the paper is to study how any trend estimates are affected by uncertainties and biases in the billion-dollar disaster data. Particular attention is devoted to the effects of the factor approach for conversion from insured to total loss. A final goal is to make recommendations concerning how the current methodology can be improved to increase the quality of the dataset.

An outline of the paper is as follows. Sources of data for disaster losses are described in Sect. 2. Next, the current method for estimating total direct loss, focusing on specific disaster examples, is presented in Sect. 3. The effects of uncertainties and biases on the detection and attribution of trends in losses are assessed in Sect. 4. Finally, Sect. 5 contains a discussion and conclusions, including recommendations for how the billion-dollar dataset can be improved.

2 Data sources

Estimating the total direct economic losses from a natural disaster event is an iterative process due to the number of datasets, public and private, needed to inform an assessment (Table 2). Economic loss estimates are often not reliable for several months to years after a major disaster due to the time it takes to receive, process and verify insurance claims in a complex post-disaster environment. Sources providing insured loss data following a

Table 2 An overview of the metadata behind the data sources used in the billion-dollar event analysis

	ISO/PCS	FEMA (PDD)	FEMA (NFIP)	USDA/RMA	Army corps	NIFC	State agencies
Data	*Provided:* Residential Commercial property-interruption Vehicles (insuredw/ comprehensive)-Boats Inland marine *Not provided:* Agriculture, Flood losses, Aviation & Marine, Loss above limits	*Provided:* Government disaster assistance, debris removal, financial aid Public Assistance, Housing Assistance, Individual Assistance, Small Business loan Assistance	*Provided:* Insured flood loss for residential and commercial properties	*Provided:* Insured multi-peril crop/livestock insurance payouts, crop progress and quality reports market value of crop production	*Provided:* Annual flood event summaries and major flood event reports that detail levee damage, other damages	*Provided:* Wildfire losses to structures, commercial timber, wildfire suppression costs	*Provided:* Estimated agribusiness losses, forestry, fishing, Surveyed % of properties with multi-peril and flood insurance, etc.
Disaster categories included	Tropical Cyclone Severe Storm Winter Storm Wildfire	Tropical Cyclone Severe Storm Winter Storm Wildfire Flooding Crop Freeze	Flooding	Tropical Cyclone Severe Storm Winter Storm Wildfire Drought/Heat Flooding Crop Freeze	Flooding	Wildfire	Tropical Cyclone Severe Storm Winter Storm Wildfire Drought/Heat Flooding Crop Freeze
Temporal period	1949-present	1964-present 1989-present	1968-present	1948-present 1989-present	1983-present	1960-present	Regarding a specific disaster event
Spatial resolution	State-level	State-level County-level	State-level	State-level County-level	River-basin, State-level	Region, State, county (depending on data product)	State-level

Table 2 continued

	ISO/PCS	FEMA (PDD)	FEMA (NFIP)	USDA/RMA	Army corps	NIFC	State agencies
Data sources	Surveys of insurers, market share analysis, air/ground damage surveys, interviews, etc.	State and local disaster needs/ grants	Flood insurance payouts	Farmer and field surveys; data from partner insurance companies	Floodplain, household and business surveys	Fields reporting, state and local fire authorities	Local and State farm reporting to USDA; city/ state damage assessment
Change in recording threshold	\$1 M (1949–1981) \$5 M (Jan. 1982–1997) \$20 M (Jan. 1997-present)	County/per capita indicators adjusted each fiscal year to reflect changes in CPI. Assists in FEMA's evaluation of disaster impact at county-scale (e.g., \$2.83, \$2.94)	Single-family dwelling limits: 1977–1994 Structure \$150 k Content:\$50 k 1994–2009 Structure \$250 k Content:\$100 k Policy revisions were enacted in 1973, 1977, 1994, and 2004	Insurance policy changes and additions are complex. Many programs (SURE, NAP,LIP) offer assistance from 50 % - 85 %.Major crop insurance policy revision in 1994		Stats after 1983 were compiled by states and agencies. Stats before 1983 under reanalysis	

disaster include 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) and Risk Management Agency (RMA).

Each of these data sources provides unique information as part of the overall disaster loss assessment. However, there is variance in what information is available for specific disaster types. Table 2 is partitioned by the data sources we use to quantify the direct losses resulting from weather and climate disasters and the metadata attributes for each of the data sources. This includes the data source disaster loss variables, the temporal period and spatial resolution of the data, report update cycles, changes in recording thresholds and the collection sources used to develop the data. For example, the ISO/PCS source provides insurance loss data for tropical cyclones, severe local storms, winter storms and wildfires, but not drought, crop freeze or flooding, as data for those events are provided by USDA and FEMA. The loss variables included for each of the data providers are also distinct. PCS aggregates several sources of insured loss including residential and commercial property, business interruption losses, vehicles, boats, and inland marine losses, but does not include losses to agriculture, aviation, ocean marine or losses resulting from flooding. Again, these categories of insured losses are detailed by USDA and FEMA data. The cost of the premiums and loss above limits are not traditionally included, which does create an under bias in losses, but we estimate this into our un(der)insured (i.e., uninsured and underinsured) loss adjustments, as discussed in Sect. 3.

There have also been changes in disaster definitions and coverage limits for each of these data sources. For example, in 1949, when the PCS data collection began, the insured loss threshold requirement was $1 million in damage within a single state, to be classified as a 'disaster.' This threshold increased to $5 million in January 1982 and then increased to $25 million in January 1997. The current catastrophe definition is an event causing $25 million or more of insured property damage and having affected a significant number of policyholders and insurers (ISO 2011). However, these changes do not particularly affect our analysis due to the relatively high, billion-dollar threshold.

Another example is how the FEMA/NFIP residential and commercial coverage limits have increased several times, with policy revisions enacted in 1973, 1977, 1994 and 2004 (NFIP 2010). Likewise, participation in USDA crop insurance programs has also increased through time. The largest rise in crop insurance participation occurred after the Federal Crop insurance Reform Act of 1994, which introduced the catastrophe risk protection level of coverage, in which the premiums were completely subsidized and a modest processing fee was charged for each insured crop. Perhaps most important are the general increases in insurance participation over time and the rise in value of insured property, with respect to the reported insured data. Better understanding the un(der)insured losses are a key challenge given the data.

3 Method for estimating total direct losses

3.1 Insurance data as basis for estimation

To estimate the total loss from disasters, we first consider public and private insurance coverage. Based on the data available, we employ a simplified factor method, which differs by disaster type (Table 3).

Table 3 Method for developing billion-dollar disaster event loss calculations by disaster type and data sources using a factor approach to convert from insured to total losses

Severe Storm or Winter Storm: when < \$1 billion PCS total for each state = (PCS × 1.25) + (FEMA_PDD if > PCS × 0.25)[a] + (NFIP × 4.00)[c] + (State report[d] or USDA × 2.00) + (OTHER)
Severe Storm or Winter Storm: when > \$1 billion PCS total for each state = (PCS × 1.42) + (FEMA_PDD if > PCS × 0.42)[a] + (NFIP × 4.00)[c] + (State report[d] or USDA × 2.00) + (OTHER)
Tropical Cyclone[b] = (PCS × 2.00) + (FEMA_PDD if > PCS × 1.00) + (NFIP × 1.00)[c] + (State report[d] or USDA × 2.00) + (OTHER)
Non-tropical flooding = (NFIP × 4.00)[c] + (State report[d] or USDA × 2.00) + (FEMA_PDD) + (OTHER)
Drought/Heatwaves = (State report[d] or USDA × 2.00) + (FEMA_PDD) + (OTHER)
Wildfire = (PCS × 2.00) + (FEMA_PDD if > PCS × 1.00) + (State report[d] or USDA × 2.00) + (OTHER)
Freezing Episode = (State report[d] or USDA × 2.00) + (FEMA_PDD) + (OTHER)

a Only incorporate the higher factor of PCS or FEMA_PDD in addition to original to represent underinsured loss b For hurricane wind/water damage, state reports may inform how the PCS to NFIP insurance ratio is adjusted c NFIP factor adjusted based on available data (i.e., NFIP participation rates, state or river-basin assessments, etc.) d State reports may supersede USDA crop loss data if it produces a more complete total agriculture loss estimate

3.1.1 FEMA/National flood insurance program

For example, residential and commercial flood insurance is most widely provided and managed by FEMA's National Flood Insurance Program. Mortgage lenders require any residence within FEMA 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. The NFIP market is highly concentrated, as nearly 70 % of policies are in five states—Florida, Texas, Louisiana, New Jersey and California, while Florida and Texas together represent more than 50 % of the total NFIP active policies across all states (Kunreuther and Michel-Kerjan 2011). There is also a bias in NFIP participation depending on the number of single-family houses that exist in the SFHAs where the mandatory purchase of flood insurance applies. Research by Dixon et al. (2006) found that the NFIP participation is 16 % in communities with 500 or fewer homes in the SFHA, 56 % in communities with 501–5,000 homes in the SFHA, and 66 % in communities with >5,000 homes in the SFHA zone.

Given these differences, it is necessary to account for how NFIP participation varies across states and regions. One study by PricewaterhouseCoopers (1999) found in 1997 that the nationwide market participation for the NFIP across the United States was estimated at 26 % of eligible parcels. Dixon et al. (2006) found that the chances of purchasing insurance are higher for SFHA communities subject to coastal flooding/storm surge (63 %) versus communities more at risk to riverine flooding (35 %). Flood insurance coverage drops off steeply outside of the high-risk flood areas, which is important as 25 % of all flood insurance claims come from low-to-moderate-risk areas (FEMA 2011). The Dixon et al. study details how NFIP participation varies regionally inside and outside the SFHAs, showing high degrees of variability. Participation rates in the SFHAs are relatively low in the Midwest (22 %) and Northeast (28 %) regions while higher in the South (61 %) and

West (60 %). However, NFIP policy participation outside the SFHAs in all US regions is very low (<than 10 %), as these reflect low-to-moderate flood risk areas where coverage is not required. For our own comparison of the spatial variation in NFIP penetration, we have a county-based NFIP penetration database provided to us by FEMA, but it also reflects spatial issues as discussed.

It is also important to note that commercial and residential needs for flood insurance coverage exceeding the limits of NFIP policies can be fulfilled by specialized private sector flood insurers. We rely on commercial flood losses estimates from Reinsurance companies to better understand these impacts not reported in the NFIP data. Personal and commercial vehicle flood damage is part of private comprehensive insurance, as reported by ISO/PCS. With the exception of some commercial, residential and most all vehicle policies, the NFIP underwrites US flood risk.

Given the complexity of the data, we use a regional approximation for NFIP coverage and apply a factor than corresponds with the NFIP participation rate. This seeks to adjust for total flood damage potential for those properties not covered by NFIP insurance payments. For example, if a region had approximately 25 % policy protection, we apply a factor of 4.0 to NFIP flood insurance payment totals for an inland flooding event. However, this factor is adjusted higher when widespread, prolonged flooding event takes place across a large area (e.g., 1993 Midwest Flood), in which damage has occurred beyond the SFHAs where policy coverage is very sparse.

3.1.2 ISO/Property claim services

For severe local storms where high wind and hail cause property damage, we use a different methodology. The widespread use of homeowners insurance provides coverage against many natural hazards including wind storm, hail, fire, lightning, snow, sleet, weight of ice, etc. Several surveys from the Insurance Information Institute (III) and the National Association of Insurance Commissioners (NAIC) from the early 1980s through 2011 report that 83–95 % of residences obtained covered by multi-peril insurance policies (e.g., specific to wind, hail, lightning damage). However, lower income residences often do not have insurance and the 25 % of society that rent largely do not have insurance for their possessions. Given these caveats, we have approximated that 80 % of losses will be covered during a typical severe weather outbreak, which PCS indicates is a good standard (ISO/Gary Kerney personal communication 2012). PCS data reflect the residential, commercial and vehicle claims for high wind or hail damage. As a result, we use PCS insured losses $\times$ 1.25 as one adjustment in the equation. However, not all structures have insurance coverage and others do not have enough coverage to replace structural, contents, and time element losses, which result during the most severe events. To better approximate insured losses from the most severe events causing extreme devastation (e.g., April 25–28, 2011 Southeast Super Outbreak), we approximate that only 70 % of total losses will be covered by insurance and factor PCS insured losses $\times$ 1.42. This 70 % factor is used when PCS insured loss amounts >$1 billion for a single state (CPI-adjusted) resulting from an outbreak of severe weather. This is likely a conservative standard, but reflects the larger number of structures exposed to higher amounts of loss from the most destructive severe weather outbreaks. This has happened only rarely when tornadoes or large hail affects large suburban or urban areas (e.g., May 1999 Oklahoma City, OK; May 2011 Joplin, MO).

3.1.3 USDA/Risk management agency

Our disaster loss methodology also examines USDA/RMA crop insurance data to further adjust or supplement our total loss calculations. Farmers' participation in the Federal crop insurance program is voluntary. RMA has overall responsibility for supervising the Federal crop insurance program, which it administers in partnership with the private sector. Insurance policies are sold and completely serviced through approved private insurance companies, and insurance policies cover losses due only to natural disasters. The producer selects both the percentage of yield to be covered (i.e., 50–75; 85 % coverage is available for limited crops and in limited areas) and the percentage of the commodity price (55–100 %). USDA determines whether to insure a commodity on a crop by crop and county by county basis, based on the farmer demand for coverage, level of risk associated with the crop in the region, and if sufficient actuarial data are available. The Federal crop insurance program is not available for all crops, types and practices. For commodities not insured under the federal crop insurance programs, USDA administers seven disaster assistance programs: Emergency assistance for livestock, honey bees and farm-raised fish (ELAP); Emergency forest restoration program (EFRP); Livestock forage program (LFP); Livestock indemnity (LIP); Noninsured crop disaster assistance program (NAP); Supplemental revenue assistance payments program (SURE); Tree assistance program (TAP).

Since USDA crop insurance indemnity data (loss payments) do not reflect the total value of crops damaged/destroyed during a disaster event, we have developed a factor approach. Assuming that on average 70 % of eligible acres are insured and most producers select 70 % of crop yield to be covered (USDA 2012), we approximate the total crop loss by applying a 2.0 factor to the RMA crop indemnity data; that is, $1/[(0.7)(0.7)] = 2.04 \approx 2$. However, state-issued reports following a disaster event may supersede USDA crop indemnity data factorization in our analysis if they provide greater levels of detail. For example, state agency reports on crop loss events may be more useful as they often detail USDA data on yields, acres abandoned and market price to estimate a value loss in dollars. State reports also compare the average crop yields versus lost yield due to a disaster event (NOAA 2008). States reporting often provides the following crop loss perspective: Estimated (loss \$) for each affected crop type = (Expected crop yield/acre) x (market price/acre) × (% of total acres yield loss/by crop)

For long-duration disaster events such as drought, livestock losses are also calculated by incorporating increased feeding costs, which have an aggregative effect on dairy and meat market prices. If no detailed state reports are available for a disaster, we then apply the 2.0 factor to the crop losses while also directly totaling additional losses when available (e.g., livestock, nurseries, commercial timber, etc.).

3.2 Estimating the loss from a tropical cyclone disaster

3.2.1 Basis for estimation

The first event calculation details how we account for the direct economic losses due to tropical cyclone damage. The losses are challenging to estimate as damages from wind and water (e.g., storm surge, inland flooding) are insured by different private and public entities. For example, PCS provides a reliable assessment of wind-related losses for residential, commercial, vehicle lines of property insurance at the state level. However, a total, stable PCS loss estimate can range from 6 weeks after an event to more than 1 year due to the size and complexity of the wind versus water damage and associated litigation.

State-subsidized 'wind-pools,' that act as 'insurers of last-resort' when private sector providers do not provide enough or affordable insurance in hazardous, coastal or riverine areas, are also part of the PCS state-level loss estimates. Other relevant loss data not included in PCS totals are FEMA's Presidential disaster declarations encompassing non-insured government disaster assistance. This includes public assistance (PA), individual assistance (IA), housing assistance (HA) and small business assistance (BA) for individuals, families, businesses and municipalities who are un(der)insured for initial recovery and rebuilding where appropriate (NFIP 2010). Another data source is FEMA flood insurance payments through the NFIP. However, high value structures can be only insured up to NFIP coverage limits ($250 k structure, $100 k contents) for residential and ($500 k structure, $500 k contents) for commercial regardless if the property is located in a special flood hazard area (SFHA) or not. Other sources of loss information include USDA crop indemnity payments for crops destroyed by high wind or flooding associated with a tropical cyclone and offshore infrastructure and marine losses provided by other insurance reporting such as Munich Re. Given the insurance participation variance and coverage amounts across data sources, we employ a more general approach for loss analysis.

3.2.2 Data sources and method

This methodology takes into account PCS, USDA, FEMA NFIP and FEMA PDD loss data using a factor approach modified by state-issued information. State-specific disaster reports—such as *Texas Rebounds* regarding Hurricane Ike's damage to Texas—are useful in providing guidance to adjust insured versus uninsured properties damage from wind and water losses provided by PCS and NFIP data, respectively (Texas Governor's Office 2008). Each disaster event type is adjusted differently based on approximate insurance participation and the loss data available.

In September 2008, Hurricane Ike caused widespread losses along the Texas coast and further inland from considerable storm surge and wind destruction. Severe gasoline shortages occurred in the southeast states due to damaged oil platforms, storage tanks, pipelines and off-line refineries. The final PCS insurance payout estimate for Ike was about $12.5 billion, while the National Flood Insurance Program payout was about $2.5 billion (Table 4). To better estimate the insured versus uninsured damage for both wind and water loss, we examine the NFIP coverage percentage for cities and counties in the disaster zone. The Texas Rebounds report indicates that an average of 27 % of wind damages and 61 % of flooding damages was uninsured in the Texas declared disaster zone affected by Hurricane Ike. Dividing 100 % by 73 and 39 %, representing wind and flood insured participation rates, produces factors of 1.37 and 2.56, respectively. These factors provide some guidance on how to treat the PCS and NFIP insurance payouts for Texas. We calculate a total loss of $9.8 billion $\times$ (1.37) for the 73 % PCS insured wind damage and a total loss of $2.1 billion $\times$ (2.56) for the 39 % NFIP insured flood damage, resulting in a combined subtotal of $18.8 billion.

Independent from FEMA flood insurance coverage for residential and commercial properties, we also examine FEMA disaster relief coverage for un(der)insured losses to residential, commercial and public property losses, which by law cannot replicate any other source of insurance funding (FEMA 2011). We compare FEMA emergency assistance costs with PCS insured losses for each state impacted by a disaster event to better adjust for a total loss. For example, if the FEMA public assistance, housing assistance, individual assistance and business assistance collectively exceed the PCS factor adjustment for a particular disaster type, then the FEMA total is added to the PCS insured loss total with no

Table 4 Damage/loss categories resulting from Hurricane Ike and calculations to produce a single total loss ($ Millions)

Hurricane Ike insured loss ($ Millions)	PCS combined insured loss (commercial, residential, auto)	Commercial	Residential	Automotive	FEMA (PDD) emergency assistance (PA + IA + SBA)	FEMA flood insurance payments (NFIP)
Alabama	–		–		13.1	1.7 (×1.0)
Arkansas	56.0 (×2.0)	35.0	12.5	8.5	2.5	
Illinois	240.0 (×2.0)	150.0	50.0	40.0	108.0	53.1 (×1.0)
Indiana	330.0 (×2.0)	230.0	80.0	20.0	93.0	31.2 (×1.0)
Kentucky	533.0 (×2.0)	405.0	110.0	18.0	18.9	
Louisiana	135.0 (×1.0)	50.0	50.0	35.0	263.0*	303.7 (×1.0)
Missouri	76.0 (×2.0)	50.0	16.0	10.0		42.4 (×1.0)
Ohio	1,255.0 (×2.0)	960.0	255.0	40.0	39.6	
Pennsylvania	75.0 (×2.0)	63.0	8.0	4.0		
Texas	9,800.0 (×1.37)	5,500.0	4,000.0	300.0	2,464.0	2 096.0 (×2.56)
Sub total (1)	18,691.0				263.0*	5,797.7
State aggregate losses to: Marine/Offshore Infrastructure	2,000.0					
Agriculture, forestry, fishing	825.0					
Sub total (2)	2,825.0					
Total						~27,500.0

Using Texas Rebounds insurance coverage report for cities/counties in the Texas disaster area as factor guidance

73 % insured for wind damage (27 % uninsured) = PCS $9.8 billion × (1.37)

39 % insured for flood damage (61 % uninsured) = NFIP $2.1 billion × (2.56) $2.4 billion FEMA_PDD < PCS × 0.37 factor ($9.8 B × 0.37 = $3.6 billion) for un/underinsured loss

Therefore, FEMA_PDD loss for Texas not counted toward Hurricane Ike total loss *FEMA_PDD is only counted for Louisiana since FEMA_PDD ($263.0 million) < PCS × 1.0 factor ($135.0 million) additional PCS factor adjustment applied. If the FEMA total costs for a state do not exceed a state's PCS insured losses, or if a state was not eligible for FEMA disaster assistance funds, then a PCS factor adjustment is applied to better account for uninsured and underinsured losses. After examining the reported damages from Hurricane Ike, Louisiana was the only state in which the FEMA emergency assistance costs exceeded the PCS insurance loss adjustment factor ($263 million vs. $135 million). We choose to only incorporate the higher factor of PCS versus FEMA_PDD in addition to original values to avoid double-counting un(der)insured losses. We also incorporate agriculture, forestry and fishing losses provided by state agriculture centers ($875 million) and an estimated $2 billion in damage to offshore infrastructure. After examining all the input data sources and variables using our factor approach, this yields a rough estimate of total damage of about $27.5 billion. The data uncertainty and bias associated with such losses estimates will be explored in Sect. 4 of this paper.

3.3 Estimating the loss from a crop freeze disaster

3.3.1 Basis for estimation

A second disaster event example is a multi-day freeze that damaged or destroyed billions in crop production value across nearly 1,000 US counties. This event occurred April 3–10, 2007 causing widespread sub-freezing temperatures over much of the central Plains, Midwest and South resulting in significant losses to fruit crops, field crops (particularly wheat) and the ornamental industry. Temperatures in the teens and 20s (°F) accompanied by rather high winds nullified most crop-protection systems. About $2.1 billion in losses was estimated. The most significant impact of this cold wave was related to the timing and duration of the event in parallel with ongoing crop development (NOAA 2008). Most affected were the blooming fruits across parts of the Midwest and South, winter wheat crop across the central Plains and Midwest and the emerging corn in the South.

3.3.2 Data sources and method

The agricultural impact data for the April 2007 freeze event are summarized from official USDA information, including the *Crop Production* report, *Crop Progress* summaries and state-specific disaster reports. Since each crop type has varying levels of coverage availability (50–85 %) across specific USDA insurance programs (e.g., SURE, NAP, LIP), the USDA indemnity payments do not reflect the total crop value lost due to a disaster (USDA, 2012). Moreover, since not all crop types are insured and not all farmers seek coverage for their crops, the state agency reports on crop loss for the 2007 freeze are more useful as they detail the percentage of crop yield loss (by crop type) multiplied by respective market price that were not produced due to damage from the freeze event (Table 5). After examining many states impacted by this event, we participated in producing a national report to more closely estimate the total loss to crop production as a result of the freeze. For each state affected by the April 2007 freeze, we employed the following calculation:

For each crop type, the estimated crop loss = (Expected crop yield/acre) × (market price/acre) × (% of total acres yield loss/by crop)

Aggregating the crop losses for each affected crop type across all affected states results in a total loss of about $2.1 billion (Table 6).

The total crop loss estimation is conservative, as it was based on information available to state agricultural centers/specialists at the time and is subject to update, which is the case

Table 5 Estimated loss crop valuation example from April 2007 freeze episode

Crop	Acres	Yield/acre at price	Gross return/acre ($Thousands)	Est. crop value ($Millions)	Est. crop loss(%)	Est. loss from freeze event ($Millions)
Apple	1,000	400 bu/Acre * $20.50/bu	8.2	8.2	90	7.4
Blackberries	110	4,000 qt * $2.00/qt	8.0	0.9	90	0.8
Blueberries	120	6,800 pt * ($1.25) 1,700 pt * ($1.50)	11.1	1.3	90	1.2
Grapes	400	6.2 Tons/Acre * $0.50/lb	6.2	2.5	60	1.5
Peaches	500	280 bu/Acre * $20.00/bu	5.6	2.8	98	2.8
Pears	30	400 bu/Acre * $20.00/bu	8.0	0.2	100	0.2
Strawberries	210	8,000 lb * $1.75/lb	14.0	2.9	50	1.5
Total	2,370			18.8		15.4

for many large-scale, destructive disaster events we analyze. In some instances, these estimates can deviate from USDA values due to altering assumptions in making the estimates. In general, only direct losses to the freeze were included, avoiding indirect losses such as lost jobs from the reduced demand for field workers to harvest crops. Also, the rise in USDA crop insurance coverage and participation along with the rising crop production and market values skew the crop loss comparisons over time for different events. The next section will include the exploration of this issue in more detail for the major US crops (i.e., corn, soybeans, wheat), which collectively account for over half the US annual crop production value.

4 Effects of uncertainties and biases on trend analysis of billion-dollar disasters

In this section, we consider the effects of potential uncertainties and biases identified in Sects. 2 and 3 on the detection and attribution of trends in the annual frequency of (and annual aggregate loss from) billion-dollar disasters. As background, we first perform a trend analysis of the billion-dollar disaster dataset.

4.1 Trend analysis of billion-dollar disasters

The probability distribution of losses has a high degree of positive skewness (Jagger et al. 2011; Willoughby 2012), with a few disasters dominating the aggregate loss (e.g., 20 % of the hurricanes striking the United States have caused nearly 90 % of the total loss; Katz 2012). In part for this reason, it is difficult to distinguish between year-to-year variations and long-term changes, particularly when only considering billion-dollar disasters. If the inflation-adjusted losses from all extreme weather and climate events are analyzed instead, then a marked increasing trend in recent decades in the annual aggregate loss is obvious (e.g., Gall et al. 2011).

We let $N(t)$ denote the number of billion-dollar events in year t, $N(t) = 0, 1, \ldots$. Because the number of such events is relatively small, it is natural to assume that $N(t)$ has a Poisson distribution (i.e., by the so-called Law of Small Numbers), with mean (or "expected value") $E[N(t)] = \lambda(t)$, $\lambda(t) > 0$ possibly depending on the year t. As a model

Table 6 Economic crop loss totals for North Carolina commodities and total commodity losses for all US states resulting from the April 2007 freeze episode ($ Millions)

Commodity	Acres affected (Thousands)	Losses ($ Millions)	State	Losses ($ Millions)
Barley	24.8	1.2	Alabama	13.4
Corn	243.9	15.2	Arkansas	116.0
Fruit & Vegetables	21.3	31.2	Georgia	400.0
Hay	38.5	1.0	Illinois	152.4
Irish Potatoes	10.0	1.6	Indiana	48.0
Nursery	20.1	40.1	Iowa	4.0
Oats	11.0	0.6	Kansas	66.5
Pasture	71.4	0.3	Kentucky	133.5
Rye	6.7	0.3	Mississippi	29.0
Tobacco	0.2	0.6	Missouri	400.0
Wheat	275.5	13.3	North Carolina	105.4
			Ohio	155.0
North Carolina	723.4	105.4	Oklahoma	350.0
			South Carolina	39.3
			Tennessee	50.0
			Total	2,062.5

for the trend in the number of events, a linear trend in the log-transformed mean is assumed; that is,

$$\ln\lambda(t) = \lambda_0 + \lambda_1 t,$$

in part to constrain the rate $\lambda(t) > 0$. Here λ_0 and λ_1 denote unknown parameters to be estimated from the data. Figure 2 shows the results of fitting this trend model to the annual frequency of disasters using the statistical technique of Poisson regression (e.g., Katz 2002). The apparent increasing trend of about 4.8 % per year [i.e., an estimate of $\exp(\lambda_1)$] is overwhelmingly statistically significant with a P value $< 10^{-5}$, at least in part because of an unprecedented number of events in 2011 (Table 7).

We let $L_n(t)$ denote the loss from the nth billion-dollar disaster event in year t, $n = 1, \ldots, N(t)$, assuming $N(t) > 0$ (i.e., at least one event occurred). To remove the high degree of skewness in the distribution of the loss from individual disasters, the loss data are first log-transformed (because $L_n(t) \geq \$1$ billion, the transformation $\ln[L_n(t)–0.9]$ is actually used). That is, the losses from individual disasters are assumed to have a lognormal distribution (Katz 2002; Nordhaus 2010; Willoughby 2012). As a trend model for the individual losses, a linear trend in the mean of the log-transformed loss is assumed; that is,

$$E[\ln L_n(t)] = \beta_0 + \beta_1 t$$

Here β_0 and β_1 denote unknown parameters to be estimated from the data. As suggested by Fig. 3, there is no apparent time trend in economic loss from individual disasters. In fact, a least squares trend analysis estimates a very slight decreasing trend of about 0.5 % per year. [i.e., an estimate of $\exp(\beta_1)$], with a P value of about 0.74 (Table 7).

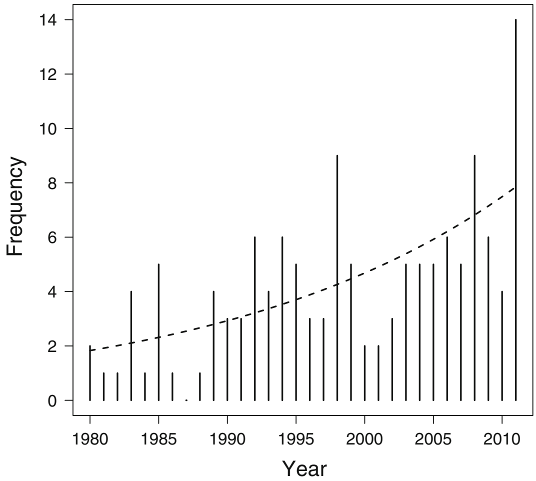


Fig. 2 Time series of annual frequency of billion-dollar disasters (*vertical bars*), along with trend (*dashed line*) fitted by Poisson regression

Table 7 Trend analysis of billion-dollar loss data

Loss component	Estimated trend	P value for trend test
Frequency	4.81 % per year	$<10^{-5}$
Individual loss	−0.50 % per year	0.740
Aggregate loss	0.200*	0.119

*Kendall's tau

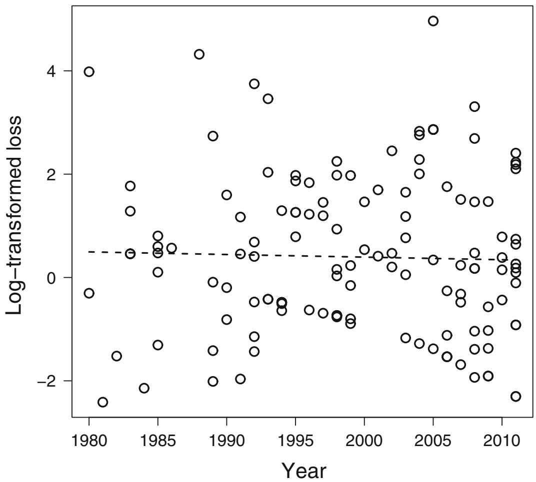


Fig. 3 Time series of log-transformed loss from individual disasters versus year, along with trend fitted by least squares (*dashed line*)

The aggregate loss in year t, say $L(t)$, can be expressed as

$$L(t) = L_1(t) + \cdots + L_{N(t)}(t), \text{ for } N(t) > 0.$$

In other words, it involves a sum whose number of terms is unknown a priori (termed a "random sum"; e.g., Jagger et al. 2011; Katz 2002). Variations in aggregate annual loss are attributable to two sources: (i) variations in loss from one event to another and (ii)

Table 8 Trend analysis of observed and simulated PCS log-transformed loss from individual tropical cyclones (31 events)

Loss	Estimated trend	*P* value for trend test
Observed	7.48 % per year	0.013
First simulation	7.71 % per year	0.013
Second simulation	7.72 % per year	0.008

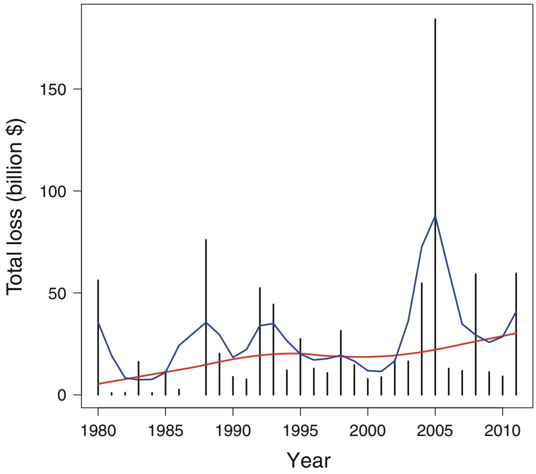


Fig. 4 Time series of aggregate annual loss from billion-dollar disasters (constant 2011 dollars, *vertical bars*), along with loess smoother (*red line*) and local smoother based on a 5-point binomial filter (*blue line*)

variations in the number of events from one year to another. From this representation of the aggregate annual loss as a random sum, the increasing trend in the frequency of disasters, along with the negligible trend in the loss from individual disasters, implies that the annual aggregate loss should exhibit a net increasing trend as well. For a random sum, a less obvious consequence of an increase in the frequency of events is an increase in the variance (or "volatility") of the aggregate loss, even with no increase in the variance of the loss from individual disasters (Katz 2002).

Figure 4 does indeed suggest the presence of a gradually increasing trend in the annual aggregate loss, particularly in the two smoothed time series based on loess (a commonly used scatterplot smoother; Cleveland 1979) and on a more local 5-point binomial filter. The plot of the unsmoothed time series suggests, perhaps, an increase in volatility as well. Because the probability distribution of a random sum is complicated (in this case, involving a combination of the Poisson and lognormal distributions), Kendall's tau, a nonparametric test for trend, is applied instead of a parametric trend model (Helsel and Hirsch 1993; Hollander and Wolfe 1973; Villarini et al. 2009). This test indicates only borderline statistical significance (*P* value about 0.12), notwithstanding the unprecedented aggregate loss in 2005 (Table 7).

4.2 Uncertainties and biases

In this subsection, we focus on the two concrete examples: (i) the nature of the bias from ignoring variations in the insurance participation rate in the case of PCS and NFIP losses for tropical cyclones and its effect on trend analysis and (ii) the sources of increasing trends in USDA insured crop losses. Although it might be anticipated that any systematic bias would be negligible, it turns out that non-negligible bias can be inadvertently introduced into the loss data.

4.2.1 Effect of variation in insurance participation rate on estimated losses

4.2.1.1 Uncertainty analysis technique As discussed in Sect. 3, economic loss from an individual weather or climate disasters are generally based on insured losses. To estimate the total direct economic loss from a disaster (i.e., both insured and uninsured losses), insured losses are inflated by a factor representing the reciprocal of the insurance market participation rate. That is,

$$L_{\text{Total}} = L_{\text{Insured}}/R,$$

where L_{Total} denotes the total economic loss from a disaster, L_{Insured} the insured loss, and R the participation rate, $0 < R < 1$. Typically, the rate R is assumed constant over an entire region and the factor $1/R$ is usually rounded (e.g., to the nearest integer), as in the examples described in Sect. 3.

From statistical theory, we know that acting as if the participation rated R is fixed (when, in fact, it varies) will lead to an underestimation of loss on the average. Formally, because the reciprocal (i.e., $1/R$) is a convex function of R, Jensen's inequality (e.g., Berger 1985, Chapter 1) implies that

$$1/E(R) < E(1/R).$$

If we further assume that the participation rate R is probabilistically independent of the insured loss L_{Insured} (a reasonably plausible assumption, at least to a first approximation), then it follows that this systematic underestimation holds for losses as well; that is,

$$E(L_{\text{Insured}})\,[1/E(R)] < E(L_{\text{Total}}).$$

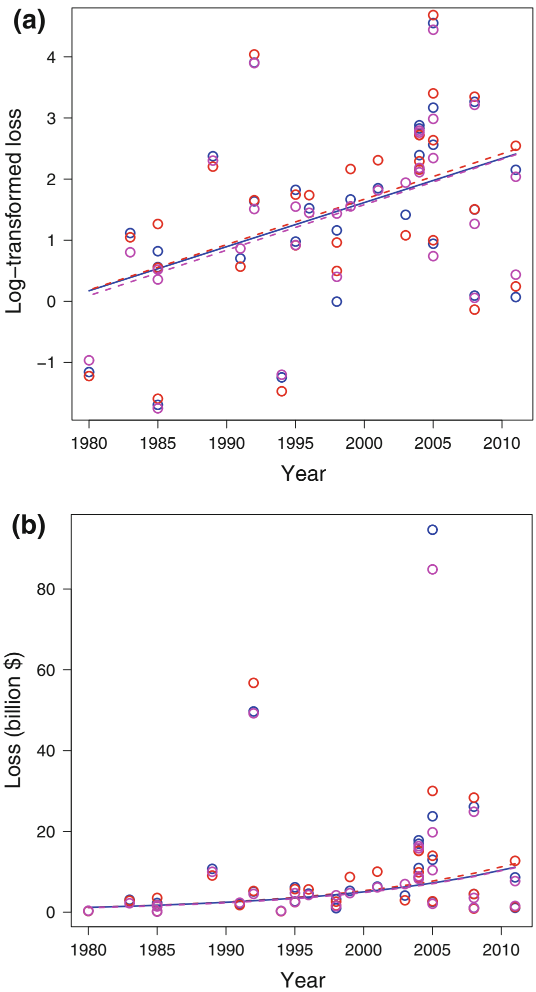
The following examples serve to illustrate the magnitude of this underestimation and its effects on trend analysis.

4.2.1.2 PCS losses from tropical cyclones In the case of PCS losses from individual cyclones, the factor of two (i.e., $R \approx 0.5$) is typically used (for simplicity and lacking more specific data) by the National Hurricane Center for approximating hurricane loss (see Sect. 3). This factor may well be consistent with the average rate of insurance participation along the portions of the U.S. Gulf and Atlantic coasts most vulnerable to tropical cyclones. Nevertheless, this rate varies considerably along the coast for a number of reasons (Major 1999; Vellinga and Mills 2001). We consider the effect of this variation on the estimated total economic loss from tropical cyclones, including in terms of trend analysis.

As a crude approximation to the observed variation in participation rate, we assume that R has a beta distribution on the interval (0.25, 0.75) with both shape parameters $p = q = 2$ (Chapter 24, Johnson and Kotz 1970). This distribution has a mean $E(R) = p/(p + q) = 0.5$, and with roughly a 50 % chance of R falling between 0.4 and 0.6. Simulated total losses are created through dividing each of the 31 PCS observed insured losses by a pseudo random value of the participation rate generated from this beta distribution.

Figure 5a shows the log-transformed observed PCS losses (inflated by a factor of two) from individual tropical cyclones, along with the corresponding synthetic losses from two

Fig. 5 **a** Log-transformed observed and simulated PCS loss from individual tropical cyclones, along with fitted linear trend lines, blue indicating observed values, red and pink the two simulations. **b** Observed and simulated PCS loss from individual tropical cyclones, along with fitted trend curves (based on linear trends for log-transformed loss), blue indicating observed values, red and pink the two simulations



simulations using the beta distribution to take into account uncertainty about the insurance participation rate. Figure 5b shows the corresponding untransformed losses. On average, the underestimation of loss when the participation rate is taken to be constant at 0.5 is roughly about 11 % (estimated from 100,000 simulations from the beta distribution).

Table 8 shows the results of fitting a linear trend to the log-transformed observed losses, as well as to the two simulated data sets. The three fitted trend lines are included in Fig. 5 as well. The systematic underestimation of loss is too small relative to the variation in losses to be evident in the figures with only two simulated time series. Moreover, this bias seems to have hardly any effect on the estimated slope of the trend line or on its statistical significance. These results about underestimation bias and insensitivity of the trend analysis are not very sensitive to the particular choice of values of the parameters of the beta distribution.

4.2.1.3 NFIP losses from tropical cyclones In contrast to PCS data, the participation rate for NFIP is more variable. As noted in Sect. 3, in practice, the factor is varied depending on the region where the tropical cyclone strikes, but still rounded off with typical values being 1, 2, 3, 4, 5 or 6 (as inferred from the NFIP loss data for 19 US tropical cyclone events from 1989 to 2008). To approximate the mean factor of about 2.85 over these 19 events, we use a beta distribution with parameters ($p = q = 1.25$) on the interval (0.05, 0.95) to represent the distribution of the corresponding participation rate. We also used a beta distribution with $p = q = 1$on the interval (0.05, 0.95) to reflect the actual granularity of NFIP participation rate within the region (Michel-Kerjan et al. 2011). These values of the parameters of the beta distribution are necessarily smaller than those used for the PCS data (i.e., $p = q = 2$) because of the greater variation in participation rates.

Based on 100,000 simulations from each of the two beta distributions, the results indicate a loss underestimation of about 5.2 % from rounding participation rates. Further underestimation of about 9.7 % results from ignoring variation in participation rates within regions. Combining these two sources of bias yields a total loss underestimation of approximately 15.4 %. This underestimation bias can again be explained by repeated application of Jensen's inequality. It appears to have only a small effect on trend estimation of NFIP losses (Fig. 6a, b; Table 9). Again, these results are not sensitive to the exact form of beta distribution.

4.2.2 Sources of increasing trends in insured crop loss

As described in Sect. 2, USDA crop insurance loss data have many complicating factors including increasing policy participation, insured acreage, value of crops, number of insurable crop types, changing policy structures, etc. (USDA 2011). This complexity is inherent in the top three most valuable US crops (i.e., corn, soybeans, wheat), which constitute over 50 % of the annual US crop value production. Rather than limiting our analysis to billion-dollar disasters, we analyze all of the available crop loss data to better quantify trends. It is anticipated that similar trends would arise as well (but be more difficult to detect) if attention were restricted to only crop losses associated with billion-dollar disasters.

Each of these crops shows an increasing trend in the total annual insured crop loss payments, especially rapid for corn and wheat (Fig. 7). However, if crop losses are measured relative to crop insurance liability, the annual loss trend apparently goes away (Fig. 8). Liability reflects the total insured risk value underwritten by policy. Dividing liability by the reported insured crop loss ($) per year is a commonly used measurement to analyze the temporal fluctuations of agriculture loss (Changnon and Hewings 2001). Using Kendall's tau to test for trend in the relative crop loss time series (as applied in Table 7 to other loss data), the P values are about 0.794, 1, and 0.294 for the relative loss of corn, soybeans, and wheat, respectively. So, at least for these three major crops, the trends in losses are comparable in magnitude to the trends in liability.

The yield per acre production statistics for each of these crops also has a positive trend (by far the most rapid for corn) since the end of World War II, much of which is attributable to technological innovation (e.g., Johnson 2012). Although it might be possible in principle to adjust crop losses for such trends (e.g., Lobell and Asner 2003), Mearns (1988) found difficulty in distinguishing between variations in wheat yields attributable to variations in weather and climate and those attributable to technology. Another complicating factor is the variation in crop pricing over time, affected by changes in demand (e.g., due to

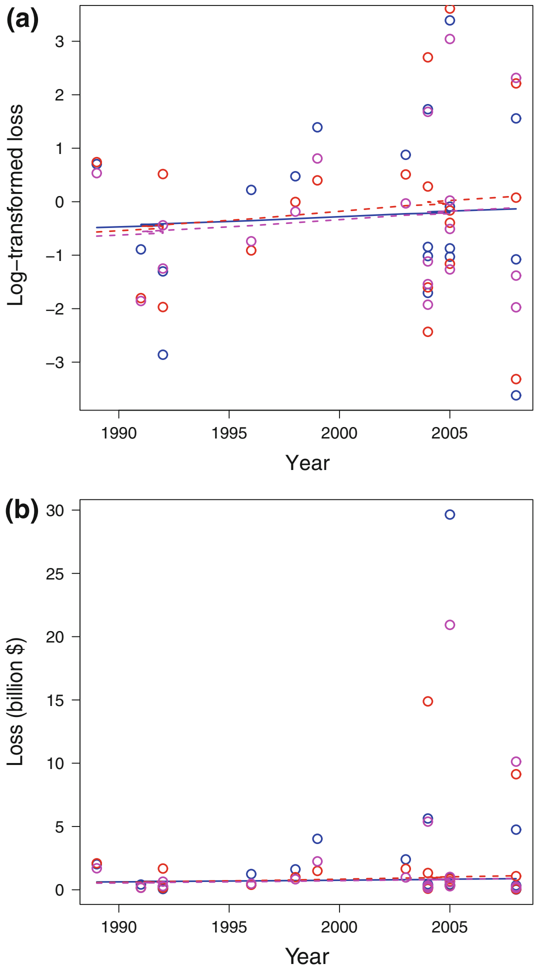


Fig. 6 **a** Log-transformed observed and simulated NFIP loss from individual tropical cyclones, along with fitted linear trend lines, blue indicating observed values, red and pink the two simulations. **b** Observed and simulated NFIP loss from individual tropical cyclones, along with fitted trend curves (based on linear trends for log-transformed loss), blue indicating observed values, red and pink the two simulations

Table 9 Trend analysis of observed and simulated NFIP log-transformed loss from individual tropical cyclones (19 events)

Loss	Estimated trend	*P* value for trend test
Observed	1.85 % per year	0.782
First simulation	3.17 % per year	0.610
Second simulation	2.83 % per year	0.623

the recent increased use of corn to produce ethanol) as well as the influence of weather and climate variations on crop production in other regions of the world. The combined effect of the identified sources contributing to increasing insured crop losses makes any attribution to weather or climate, especially for billion-dollar disasters, difficult.

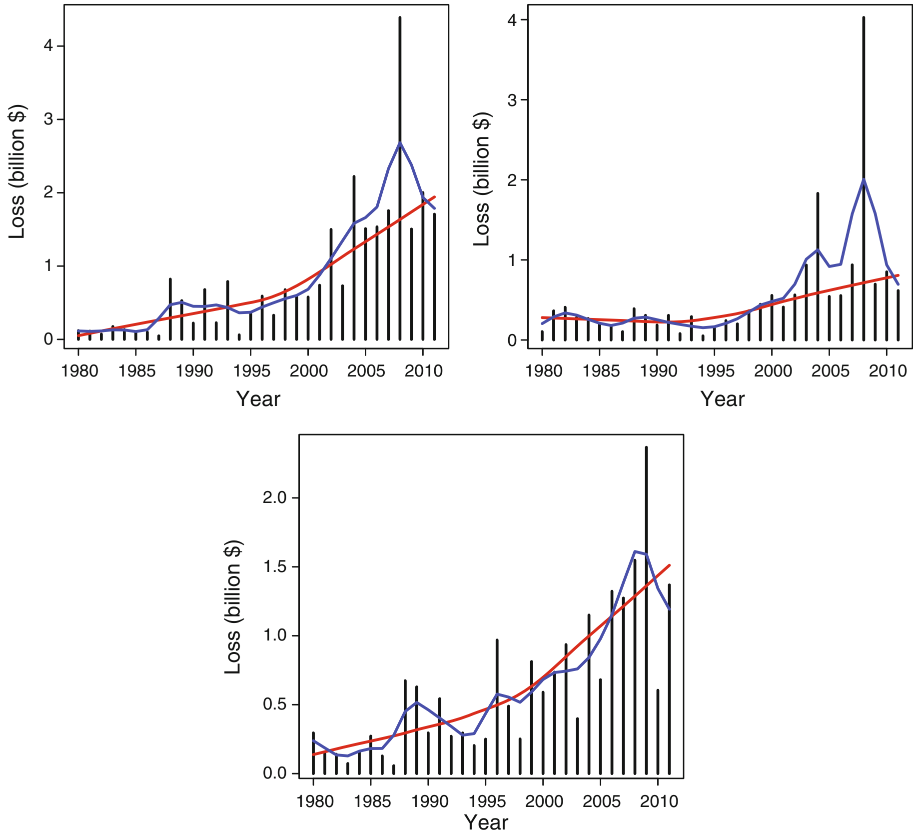


Fig. 7 Time series of annual US insured crop loss (constant 2011 dollars, *vertical bars*), for corn (*top left*), soybeans (*top right*) and wheat (*bottom*), along with loess smoother (*red line*) and local smoother based on a 5-point binomial filter (*blue line*)

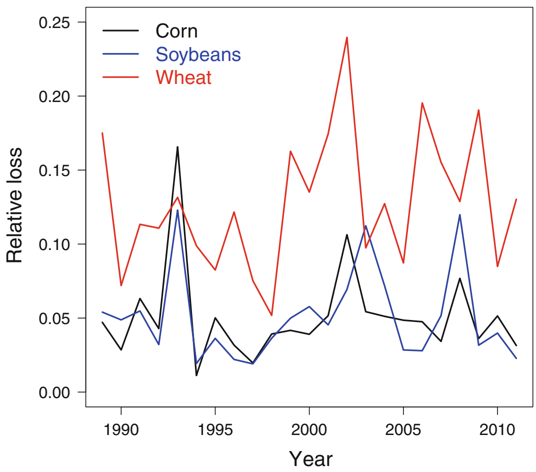


Fig. 8 Time series of USDA insured crop losses relative to crop insurance liability

5 Discussion and conclusions

This paper details the data sources and methods we currently use to develop a total direct loss estimate for several types of weather and climate events, focusing on billion-dollar disasters in the United States to our knowledge, this dataset is the most comprehensive government loss accounting effort for a variety of the most damaging US weather and climate events from 1980 to present. Being primarily based on insured losses, these loss data sources vary in quality for a variety of reasons such as increasing insurance participation, insurance liability and policy structure changes. We use a factor approach to convert insured losses into total direct losses. Potential sources of bias and uncertainty, including those associated with the factor approach, are identified.

The net effect of all biases appears to be an underestimation of average loss. As one example of the quantification of bias in loss estimation, we have shown that the historical precedent of doubling PCS losses for tropical cyclones is conservative, with an average underestimate of about 10 % for total wind-driven losses attributable to ignoring the variation in insurance participation rates. The more complicated factor adjustment process for the NFIP loss data is similarly conservative, with an average loss underestimation of about 5 % from rounding participation rates and an additional average underestimation of about 10 % resulted from ignoring variation in participation rates within regions (for a total average loss underestimation of approximately 15 %). Nevertheless, these systematic underestimations appear to have only a negligible effect on trend estimation. This underestimation of loss on average should hold, at least qualitatively, when the factor approach is applied to other loss data. Consequently, one recommendation concerning how the current methodology can be improved to increase the quality of the billion-dollar disaster dataset would be to refine the factor approach to more realistically take into account spatial and temporal variations in insurance participation rates.

USDA crop indemnity payments are another principal data source. However, this dataset has numerous complicating factors over time and space. Given resource limitations, we currently either apply a factor approach to the USDA crop indemnity payments or use published state reports, which provide a more detailed analysis on the lost value of commodities due to a natural disaster. For the major crops of corn, soybeans and wheat, increasing trends in insured losses (i.e., for all losses, not just those associated with billion-dollar disasters) are shown to be comparable in magnitude to those in liability. Given the increasing trends in yields attributable to technological innovation and given fluctuations in price, it is difficult to attribute any part of the trends in losses to climate variations or change, especially in the case of billion-dollar disasters. For the USDA crop insurance program, as well as for the FEMA NFIP, it would greatly improve the usefulness of the loss data if future insurance premiums were tied more closely to risk (Michel-Kerjan et al. 2011).

We have shown that an increasing trend in annual aggregate losses is primarily attributable to a statistically significant increasing trend of about 5 % per year in the frequency of billion-dollar disasters. But the billion-dollar dataset is only adjusted for the CPI over time, not currently incorporating any changes in exposure (e.g., as reflected by shifts in wealth or population). Normalization techniques for exposure have been limited by the lack of data on a relevant spatial scale. Yet, a number of studies have concluded that population growth, increased value of property at risk and demographic shifts are major factors behind the increasing losses from specific types of natural hazards (Downton and Pielke 2005; Brooks and Doswell 2001). The magnitude of such increasing trends is greatly diminished when applied to data normalized for exposure (Pielke et al. 2008).

Apparent increasing trends in normalized losses, aggregated across all types of weather and climate disasters have not always been tested for statistical significance (Cummins et al. 2010; Gall et al. 2011). Nevertheless, statistically significant trends are starting to emerge in some cases. For instance, at least borderline statistically significant trends in the aggregate annual loss from tropical cyclones (Barthel and Neumayer 2012), as well as in the frequency of damaging events (Katz 2010) and in the loss from individual storms (Nordhaus 2010), have been obtained. The development and implementation of normalization techniques for the billion-dollar dataset would be a challenging topic for future research.

Acknowledgments The National Center for Atmospheric Research is sponsored by the National Science Foundation. We thank Gary Kerney of ISO/Property Claims Service and Lee Messmore of USDA/RMA for providing key data sources and perspective in better understanding data caveats and limitations. We also thank a number of reviewers including Marjorie McGuirk, Neal Lott, Russell Vose, Tom Peterson, Tom Karl and Linwood Pendleton who have provided many useful comments to enhance this research article. We acknowledge two anonymous reviewers for their constructive comments.

References

Barthel F, Neumayer E (2012) A trend analysis of normalized insured damage from natural disasters. Climatic Change 113:215–237

Berger JO (1985) Statistical decision theory and bayesian analysis, 2nd edn. Springer, New York, p 617

Brooks HE, Doswell CA (2001) Normalized damage from major tornadoes in the United States: 1890–1999. Wea. Forecasting 16:168–176

Changnon SA, Hewings G (2001) Losses from weather extremes in the US. Nat Haz Rev 2:113–123

Cleveland WS (1979) Robust locally-weighted regression and smoothing scatterplots. J Am Stat Assoc 74:829–836

Cummins JD, Suher M, Zanjani G (2010) Federal financial exposure to natural catastrophe risk. In: Lucas D (ed) Measuring and managing federal financial risk, University of Chicago Press, Chicago, pp 61–96

Dixon L, Clancy N, Seabury SA, Overton A (2006) The National Flood Insurance Program's market penetration rate: estimates and policy implications. RAND Corporation, February, Santa Monica, California

Downton M, Pielke RA Jr (2005) How accurate are disaster loss data? The case of US flood damage. Nat Haz 35:211–228

FEMA (2011) Flood Insurance Manual. Revised October 2011, Available online: http://www.fema.gov/pdf/nfip/manual201110/index.pdf

Gall M, Borden KA, Emrich CT, Cutter SL (2011) The unsustainable trend of natural hazard losses in the United States. Sustainability 3:2157–2181

Helsel DR, Hirsch RM (1993) Statistical methods in water resources. Elsevier, Amsterdam, p 522

Hollander M, Wolfe DA (1973) Nonparametric statistical methods. Wiley, New York, p 503

ISO Property Claims Services (2011) Available online: http://www.iso.com/Products/Property-Claim-Services/Property-Claim-Services-PCS-info-on-losses-from-catastrophes.html

Jagger TH, Elsner JB, Burch RK (2011) Climate and solar signals in property damage losses from hurricanes affecting the United States. Nat Haz 58:541–557

Johnson DM (2012) Estimating US crop yields. Winrock International Bioenergy Workshop, Crystal City, VA. Available online: https://www.nass.usda.gov/Education_and_Outreach/Reports,_Presentations_and_Conferences/Presentations/Johnson_Winrock_12.pdf

Johnson NL, Kotz S (1970) Continuous univariate distributions—2, Wiley

Katz RW (2002) Stochastic modeling of hurricane damage. J Appl Meteorol 41:754–762

Katz RW (2010) Discussion on "Predicting losses of residential structures in the state of Florida by the public hurricane loss evaluation model" by S. Hamid et al. Stat Method 7:592–595

Katz RW (2012) Economic impact of extreme events: an approach based on extreme value theory. In extreme events: observations, modeling and economics, M. Ghil, J. Urrutia-Fucugauchi, and M. Chavez (eds), Geophysical Monograph Series, American Geophysical Union (accepted for publication)

Kunreuther H, Michel-Kerjan E (2011) At war with the weather, Paperback edn. MIT Press, Cambridge

Lobell DB, Asner GP (2003) Climate and management contributions to recent trends in US agricultural yields. Science 299, 1032

Major JA (1999) Index hedge performance: Insurer market participation and basis risk. In: Froot KA (ed) The financing of catastrophe risk. University of Chicago Press, Chicago, pp 391–432

Mearns LO (1988) Technological change, climatic variability, and winter wheat yields. Ph.D. thesis, University of California, Los Angeles (available as National Center for Atmospheric Research Technical Note, NCAR/CT-111)

Michel-Kerjan E, Lemoyne de Forges S, Kunreuther H (2011) Policy tenure under the US National Flood Insurance Program (NFIP). Risk Analysis, doi:10.1111/j.1539-6924.2011.01671.x

Munich Re (2012) Severe weather in North America, perils, risks, insurance. Munich Re Group, Munich, p 274

NCDC (2012) Billion-Dollar Weather/Climate Events. Available online: http://www.ncdc.noaa.gov/billions

NOAA (2008) The Easter Freeze of April 2007. A NOAA/USDA Technical Report. 2008-01, pp 47 http://www1.ncdc.noaa.gov/pub/data/techrpts/tr200801/tech-report-200801.pdf

Nordhaus WD (2010) The economics of hurricanes and implications of global warming. Climate Change Economics 1:1–20

Pielke RA Jr, Gratz J, Landsea CW, Collins D, Saunders MA, Musulin R (2008) Normalized hurricane damage in the United States: 1900–2005. Nat Haz Rev 9:29–42

PricewaterhouseCoopers (1999) Study of the economic effects of charging actuarially base premium rates for pre-FIRM structures

Texas Governor's Office (2008) Texas rebounds helping our communities recover from the 2008 Hurricane Season, November 2008, pp 41. Available online: http://governor.state.tx.us/files/press-office/Texas-Rebounds-report.pdf

USDA/RMA Summary of Business and NASS Principal Crop Acreage (2012) Available online: http://www.rma.usda.gov/data/sob.html

Vellinga P, Mills E (2001) Insurance and other financial services. IPCC Third Assessment Report, Working Group 2. Cambridge University Press, Cambridge, pp 417–450

Villarini G, Serinaldi F, Smith JA, Frajewski WF (2009) On the stationarity of annual flood peaks in the continental United States during the 20th century. Water Resour Res 45:W08417. doi:10.1029/2008WR007645

Willoughby HE (2012) Distributions and trends of death and destruction from hurricanes in the United States, 1900–2008. Nat Haz Rev 13:57–64