WHEN DO LOSSES COUNT?

Six Fallacies of Natural Hazards Loss Data

BY MELANIE GALL, KEVIN A. BORDEN, AND SUSAN L. CUTTER

Natural hazards loss data collected by multiple agencies for diverse purposes have varying levels of detail, yet end users are often unaware of biases in these databases and accept the loss figures uncritically.

The insurance industry has a better understanding of economic losses suffered from natural hazards than the U.S. government despite the multitude of federal agencies that focus on natural hazards. In contrast to insurance companies—most notably reinsurers—the United States has no central repository where comprehensive information on direct, indirect, insured, and/or uninsured losses caused by natural hazards is stored (Cutter et al. 2008). Federal agencies such as the U.S. Geological Survey (USGS), the National Weather Service (NWS), or the Federal Emergency Management Agency (FEMA) each collect a subset of information on a select group of hazards depending on the agency's mission.

The monitoring and collection of loss data from natural hazards is a piecemeal approach lacking in standardized procedures, leadership, resources, and political commitment (Cutter et al. 2008; National Research Council 1999). Currently, only a few U.S. agencies gather loss information—aside from ad hoc assessments during catastrophic events. The NWS, for example, generates crude estimates of direct losses caused by weather events and publishes this information monthly through the National Climatic Data Center (NCDC) as the *Storm Data* publication and the *Storm Data* online database, whereas FEMA maintains records on insured flood losses and paid claims through the National Flood Insurance Program (NFIP; FEMA 2007). The lack of a full-cost accounting system of losses leaves the nation with no clear understanding of the costs of natural hazards to communities, the environment, or the economy (Brown Gaddis et al. 2007). We also have no baseline information for assessing whether mitigation strategies and policies are effective in reducing losses. Despite long-standing and repeated calls for establishing such a systematic accounting of hazard losses for the nation (Cutter 2001; Mileti 1999; National Research Council 1999), none currently exists.

To make matters worse, existing loss data exhibit numerous biases, which end users are rarely aware

AFFILIATIONS: GALL—Stephenson Disaster Management Institute, Louisiana State University, Baton Rouge, Louisiana; BORDEN—Environmental Studies/Department of Geography, Colgate University, Hamilton, New York; CUTTER—Department of Geography, Hazards and Vulnerability Research Institute, University of South Carolina, Columbia, South Carolina
CORRESPONDING AUTHOR: Dr. Susan L. Cutter, Department of Geography, University of South Carolina, 709 S Bull Street, Columbia, SC 29208
E-mail: scutter@sc.edu

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of when using and interpreting hazard loss information. Many of these biases become apparent when comparing loss estimates for the same hazardous events across different databases. For instance, NCDC reports losses associated with Hurricane Katrina as high as $125 billion (NCDC 2008a), while the Spatial Hazard Events and Losses Database for the United States (SHELDUS) maintained by the Hazards and Vulnerability Research Institute (HVRI) at the University of South Carolina approximates the losses at around $80 billion. How can these estimates differ so dramatically for the same event? This paper highlights some common limitations associated with loss data by describing potential biases in the data, how these affect the loss statistics, and how they potentially lead to misinterpretations of the loss information.

FROM BIAS TO FALLACY. Biases in loss information often go undetected by end users and are generally a product of the type of information stored in a database and its construction. We delineate six major biases that alone or in combination skew the interpretation of loss information and eventually lead to a number of common misperceptions or fallacies about hazard events and loss information. These include the following:

1) Every hazard type is represented in loss estimates (hazard bias).
2) Losses are comparable over time (temporal bias).
3) All losses, regardless of size are counted (threshold bias).
4) All types of losses (monetary, human, direct, indirect, insured, and uninsured) are included (accounting bias).
5) Hazard losses are comparable across geographic units (geography bias).
6) Losses are the same regardless of the database used (systemic bias).

These six misconceptions are illustrated using data presently available in four widely used nonproprietary, Web-based databases: the Emergency Events Database (EM-DAT), the Natural Hazards Assessment Network (NATHAN), SHELDUS, and the Storm Events database. Although each database records hazards-related losses, they are not identical in terms of spatial and temporal coverage, unit of analysis, loss information, or other parameters (Table 1). Most of these differences originate in the initial purpose and intended target audience that each database was designed to meet. For example, EM-DAT (CRED 2008) and NATHAN (Munich Re 2008a) address a global community and contain information on major international disasters. The unit of analysis in both databases is the country level. On the other hand, SHELDUS (HVRI 2008) and Storm Events (NCDC 2008b) only include hazard events that affected the United States, generally recorded at the county level.

This paper highlights generic biases that apply to hazard databases and illustrates them using examples drawn from the four publicly accessible databases. Contrasting the selected databases serves only illustrative purposes and says nothing about the quality, comprehensiveness, or accuracy of each database. Furthermore, we note that NATHAN is in fact a subset of Munich Re's proprietary natural hazard loss database MR NatCatSERVICE and represents less than 10% of the more than 25,000 events held in MR NatCatSERVICE (Munich Re 2008b). It is not the goal of the authors to evaluate the underlying NatCatSERVICE database given its exclusive proprietary nature. We included NATHAN in our study because, Munich Re considers NATHAN "helpful in making holistic evaluations of specific locations" (Munich Re 2008c).

We use cumulative losses of historic events that affected the United States from 1960 through 2005 as our point of comparison. The monetary losses are adjusted to 2005 dollars using the average Consumer Price Index as released by the U.S. Bureau of Labor Statistics (www.bls.gov/cpi/home.htm). With the exception of SHELDUS, no database offered the ability to download inflation-adjusted losses.

Hazard bias. Hazard bias refers to the over- or underrepresentation of certain hazard types within a database. It is introduced by selective reporting of a particular hazard type (e.g., floods, weather hazards, or geophysical hazards). Hazard bias is linked to an agency's as well as a database's purpose and audience and results in over- or underreporting particular types of hazard events. A prominent example is the apparent overrepresentation of flood events in SHELDUS and Storm Events due to data collection procedures implemented by the NWS. Based on requests from the U.S. Army Corps of Engineers, the NWS is obliged to provide monetary loss estimates for any flood event even if the damage assessment is a "guesstimate" (NWS 2007, p. 12). For all other hazard types, NWS officials either use "actual dollar amounts, if a reasonably accurate estimate from an insurance company or other qualified individual is

Table 1. Comparative overview of four widely used, internet-based hazard loss databases (CRED 2008; HVRI 2008; Munich Re 2003, 2008a; NCDC 2008).

	EM-DAT	NATHAN	SHELDUS	Storm Events
Spatial coverage	Global	Global	United States w/o Guam, Puerto Rico, and other U.S. territories	United States including U.S. territories
Spatial resolution	Country	Country	U.S. county	U.S. County, U.S. regions, U.S. forecast zones
Audience	Humanitarian aid community	Insurance industry	Emergency management and hazard mitigation community	Climatology community
Type of losses	Injuries, fatalities, affected, homeless, insured damages, reconstruction costs, total damages	Economic losses, fatalities	Direct property and crop losses, injuries, fatalities	Direct property and crop losses, injuries, fatalities
Temporal	1900–present	1811–present	1960–present*	1950–present**
Coverage lag time	90 days	n/a	~180–600 days	90–120 days
Update interval	Quarterly	Continuously	Annually	Monthly
number of U.S. records (1960–2005)	623	164	>400,000	≥1,000,000 (est.)
Number of total records	≥16,000	>2,600	>400,000	≥1,000,000 (est.)
Recording thresholds	≥10 fatalities, ≥100 affected, declaration of state of emergency, or call for international assistance	Major natural catastrophes	1960–1995: ≥$50,000 crop or property losses, since 1996: ≥$1 or fatalities ≥1	No thresholds
Accessibility	Download (.xls)	View	Download (.txt)	View
Data sources	U.N. agencies, national governments, Red Cross, World Bank, reinsurers, Associated Foreign Press, etc.	MR NatCatSERVICE, national insurance associations, insured, press and news agencies, national weather services, etc.	NCDC Storm Data USGS	NWS, NCDC *Storm Data*, NOAA's Storm Prediction Center
Natural hazards				
Landslides	+	+	+	
Winter weather	+	+	+	+
Heat	+	+	+	+
Drought	+	+	+	+
Severe weather	+	+	+	+
Wind			+	+
Floods	+	+	+	+
Tornadoes	+	+	+	+
Hurricanes	+	+	+	+
Fires	+	+	+	+
Earthquake	+	+	+	
Volcano	+	+	+	
Tsunami	+	+	+	+
Technological hazards	+			
Biological hazards	+			
Ownership	Center for Research on the Epidemiology of Disaster, Catholic University of Louvain	Munich Re Group	Hazards and Vulnerability Research Institute, University of South Carolina	NCDC (NOAA)
URL	www.emdat.be	mrnathan.munichre.com	www.sheldus.org	www4.ncdc.noaa.gov/cgi-win/wwcgi.dll?wwEvent~Storms

* SHELDUS version 6.1 covers currently the time period from 1960 through May 2007.

** Only tornadoes records date back to 1950. Thunderstorm wind and hail events data back to 1955. The records of all other meteorological events start in 1993. The NCDC online database relies on the NWS hard copy publication *Storm Data*, which contains records all meteorological events dating back to 1950.

+ Hazards included in each database

available" (NWS 2007, p. 12), or do not provide an estimate at all. The mandate to include loss information on every flood event and not provide loss estimates for other hazard types leads to an imbalance in recorded losses between hazard types.

Another example is drought hazards, which are notoriously underreported (Peterson et al. 2008; Svoboda et al. 2002). The general lack of physical damage combined with a lengthy duration and its mostly agricultural impact make it extremely difficult for NWS officials to prepare spatially and monetarily correct loss estimates. According to SHELDUS, NATHAN, and EM-DAT, droughts account for less than 7% of total losses from natural hazards since 1960 (Fig. 1). This underscores the underreporting of drought losses or reveals the seemingly "marginal" impact of drought hazards.

A more subtle form of introducing hazard bias arises from issues of the definition of the hazard and assigning loss estimates (by the original data source) to predefined hazard categories within a database. This is most apparent in the management of complex events

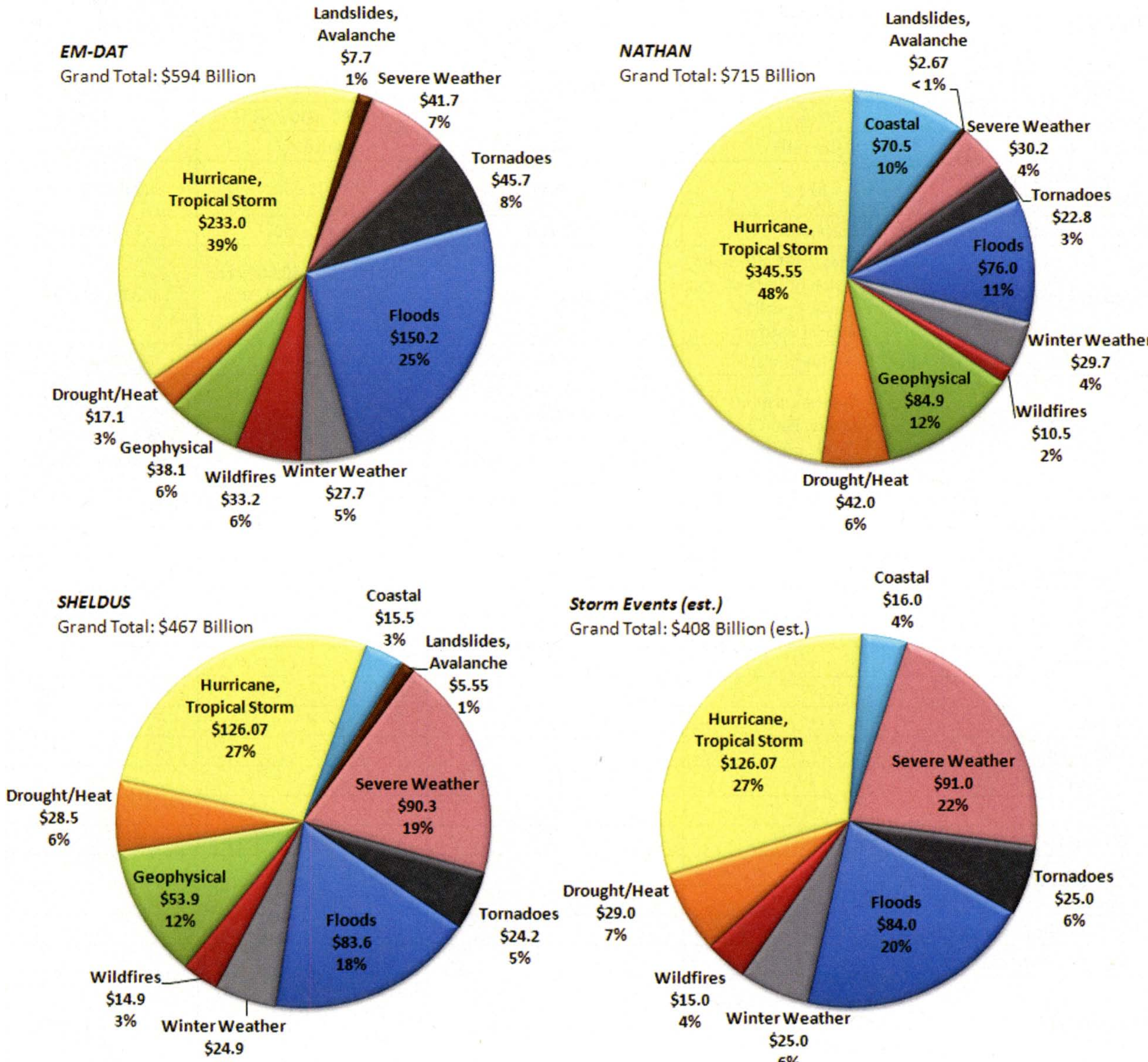

Fig. 1. Discrepancies in loss estimates (in 2005 billions) by major natural hazard type for different hazard databases (in 2005 billions) for the time period 1960–2005. The coastal category includes storm surge and coastal erosion. Geophysical events include earthquakes, volcanic eruptions, and tsunamis. The severe weather category includes wind, rain, hail, and lightning events. The loss distribution for Storm Events is hypothetical and was based on SHELDUS, which uses the same underlying data source for meteorological events (NCDC *Storm Data* publication) as Storm Events.

involving multiple hazards versus a singular hazard event. A tornado spawned by a hurricane is counted as a unique tornado event, but it could also be lumped together within the entire hurricane event, or both. Each loss database classifies events differently, especially when they involve multiple hazard types (Guha-Sapir and Below 2002). Inconsistent naming conventions and classification methodologies aggravate this problem and can result in different (and/or artificial) hazard categories for similar, if not identical events. For example, Downton et al. (2005) reveal a $520 million "flood" loss in FEMA's database that was not in the NWS data. The discrepancy is a result of differences in how each agency defines what constitutes a flood event. In this case, the event (storm surge) was outside NWS's definition of a flood.

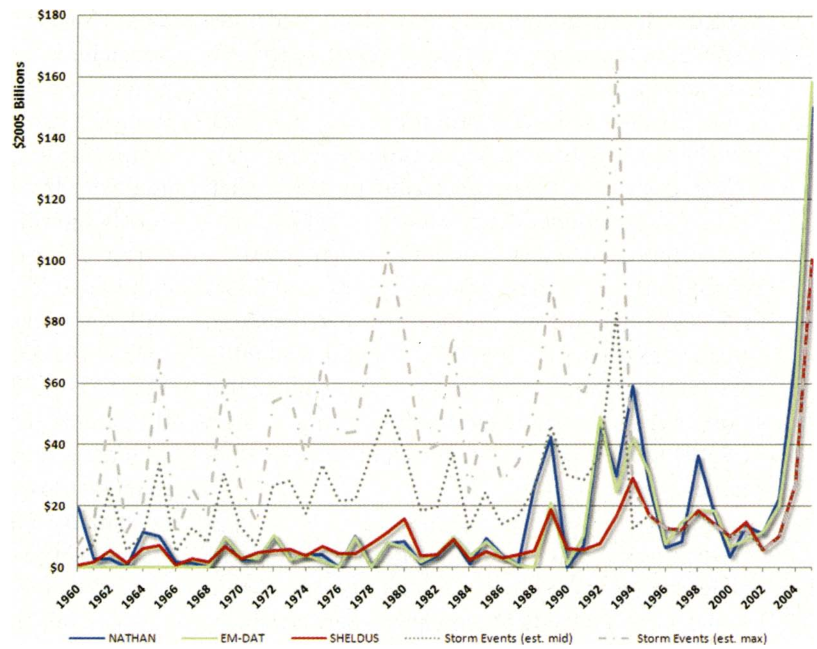

FIG. 2. Differing loss estimates for the United States (in 2005 billions) due to temporal, geographic, accounting and threshold biases. The timeline(s) for Storm Events are estimated and were derived from SHELDUS given the databases' common data source for meteorological events (NCDC *Storm Data*). The estimated timelines for Storm Events prior to 1995 reflect the midpoint (mid) and maximum (max) value of Storm Events' logarithmic loss categories.

Definitional inconsistencies between databases and between the original loss data source and the database are also a problem. A good example is hurricane-induced storm surge. In SHELDUS, storm surge falls into the "coastal" hazards category while Storm Events assigns it to a category called "Ocean & Lake Surf." Users interested in losses associated with, for instance, Hurricane Katrina, would only receive a partial loss estimate by querying the two databases for hurricanes and tropical storms, since storm surge was not included under that category. Finally, disaggregating complex events into their constituent parts could result in double or triple counting some events (e.g., hurricane wind, storm surge, and a tornado that came from the hurricane counted as three separate events).

Temporal bias. Natural hazard losses exhibit an upward trend over time (Fig. 2). This is a function of increases in wealth and population (Cutter and Emrich 2005; Pielke et al. 2008) but is also attributed to better loss accounting in recent years. The escalating pattern of hazard losses is therefore partially an artifact of advances in reporting losses, but how much or how little this effect contributes to the skyrocketing losses in comparison to effects of population growth and increasing wealth in high hazard areas is unclear.

As Guha-Sapir and Below (2002) note, disaster databases have generally converged over time with respect to data quality. This recognition implies that the further back in time users attempt to obtain data, the less consistency (and hence, reliability) they can expect to find between databases. For example, flood data were collected with a high degree of regularity since the 1930s, but data collection was completely halted from 1980 to 1982 due to a reduction in federal funding. Attempts were made later on to estimate the losses over these years, but these guesses are fraught with uncertainty and contain widely varying estimates of flood damages (Downton and Pielke 2005; Downton et al. 2005).

Advancements in hazard monitoring, detection (e.g., Doppler radar), and loss reporting have advanced the level of precision and thus reliability of loss estimates over time. As Downton and Pielke (2005, p. 18) state, "Until recently, even in serious disaster, actual (however actual is defined) total damage costs were not systematically compiled by any government agency... there was no way of checking the accuracy, or even the reasonableness, of most damage estimates." To overcome this problem, FEMA established guidelines to conduct more systematic damage assessments (FEMA 1998). Similarly, the

NWS developed Storm Data preparations guidelines (NWS 2007) to streamline and systematize the loss estimation process.

Finally, loss reporting procedures are not static and change over time. A significant change in data collection procedures occurred during 1995, when the NWS transitioned from a logarithmic loss estimation approach to reporting actual dollar amounts. Subsequently, estimates of property and crop losses in NCDC's Storm Data publication switched from categorical estimates ($5,000–$50,000, $50,000–$500,000) to whole dollar figures. This change had significant implications for any loss database, such as SHELDUS that uses Storm Data as their data source.

Threshold bias. A major methodological problem is the inconsistent threshold criteria found across different loss databases (Table 1). Discrepancies between inclusion criteria contribute to wide disparities in disaster information, including the total number of events included. Clearly, the filtering process for inclusion plays a major role in the relative size of disaster loss databases, as seen in Table 1.

Whenever thresholds come into play, events of catastrophic magnitude with high human and monetary losses are better documented in loss databases than low impact events such as small-stream flooding, lightning, or hail. Thus, the loss reporting is more comprehensive for big events although loss estimates might differ among reporting sources. On the other hand, losses triggered by singular small events remain underreported due to lack of observation especially in sparsely populated areas, and purposefully excluded from some loss databases because of the threshold criteria.

The international EM-DAT database, for instance, applies a threshold of at least 10 fatalities, 100 affected people, a call for international humanitarian help, or a declaration of a state of emergency as a minimum criterion before adding an event to the database (Table 1). Many chronic events that cause monetary losses without exceeding local response capacities are not recorded in EM-DAT. Thus, this particular database has an inherent bias toward economically catastrophic and deadly events.

The exclusion of small-scale events by global databases like EM-DAT and NATHAN is less surprising considering the feasibility, management, and resources needed to compile and maintain such a large volume of data. In many respects, national compendiums, such as SHELDUS or Storm Events, should have an easier task of compiling natural hazard loss data. However, similar to EM-DAT, SHELDUS did not include events below a certain threshold for losses generated between 1960 and 1995 (at least $50,000 in either property or crop damages). This caused SHELDUS to miss many small events that are associated with human rather than monetary losses (e.g., deadly lightning strikes). In an attempt to improve the recording of small/chronic loss events, SHELDUS eliminated its monetary thresholds (after 1995) and with the release of version 6.2 added deadly events (below the $50,000 threshold) from 1960 to 1995. Thus, SHELDUS operates on two, time-dependent thresholds. From 1960 through 1995, SHELDUS includes any event equal to or larger than $50,000 in monetary losses and any event that recorded at least one fatality. From 1996, the database contains every loss-causing event as well as every fatality and injury, irrespective of the level of monetary losses.

This selective reporting process explains why SHELDUS, despite its very conservative reporting procedures and tendency to underreport historic losses prior to 1996, shows higher annual losses than EM-DAT and NATHAN during years where few or no major disaster occurred (Fig. 2). In those years (1962, 1975, 1980, 1990, and 2001) when SHELDUS estimates surpass those provided by EM-DAT and NATHAN, the annual losses from natural hazards in the United States are characterized by multiple, recurring, cumulative losses from smaller events, rather than one large major or catastrophic one. The accumulation of chronic losses finds little recognition in hazard mitigation, emergency management, and decision making, although it is often a precursor of community resilience and its ability to absorb and recover from larger events (Bruneau et al. 2003; National Research Council 2006; Tierney et al. 2001).

Accounting bias. Seemingly trivial questions to scientists but important ones to the media and the public such as what is the costliest hazard or the costliest year, generate different answers depending on the database used. Aside from differences in number of observations, the type of loss information collected is a major factor causing highly variable loss statistics. Direct losses reflect damages sustained by public infrastructure, buildings, machinery, or crops. In the case of complete destruction, direct losses are often equivalent to the replacement costs of the structure. Indirect loss is a loosely applied concept that captures anything from economic losses associated with lost revenue, business closures, lost income to societal losses (e.g., lost cultural assets and memorabilia, stress, depression, trauma), or environmental damages (e.g., loss of species and habitat, ecosystem services) (Mileti 1999). Depending on the database in question, losses are generally reported as direct monetary (observable damage to infrastructure) and indirect losses (e.g., decline in revenue, business interruption). To further complicate the accounting, economic losses can be counted at the community, state, regional, or global levels, depending on the nature and impact of the hazard event. They are also characterized as insured or uninsured.

To test differences in accounting, we looked at the costliest hazard category in the United States. While SHELDUS, EM-DAT, and NATHAN agree it is hurricanes and tropical storms, the subsequent hazard ranks are less consistent (Fig. 1). According to NATHAN earthquakes are the second most costly U.S. hazard, with an accumulation of about $85 billion in insured losses between 1960 and 2005. On the other hand, SHELDUS identifies severe weather ($90 billion) as the second costliest U.S. hazard type, whereas floods take second place in EM-DAT, with $150 billion in losses. Why are there differences in U.S. loss estimates among the databases?

First, NATHAN documents both direct and indirect economic losses, while SHELDUS only includes direct losses. In societies with a high degree of insurance penetration, losses associated with insured hazards can exceed the estimate of direct losses dramatically as seen in the loss totals of each database (NATHAN: $715 billion; SHELDUS: $467 billion; EM-DAT: $594 billion) (Fig. 1). Figure 2 vividly illustrates this where years of large discrepancies between SHELDUS and NATHAN are marked by major (insured) events—Loma Prieta earthquake (1989), Hurricane Andrew (1992), Northridge earthquake (1994), and Hurricane Katrina (2005). A similar pattern is observed between SHELDUS and EM-DAT. We speculate that EM-DAT's higher loss estimates are inflated by the inclusion of indirect loss, whereas NATHAN's higher estimates reflect more comprehensive reporting procedures by the insurance industry when compared to federal estimates of direct losses represented by SHELDUS.

Second, the insurability against the hazard impact biases the reporting. In the case of NATHAN, the loss distribution across hazard types depends largely on the insurability of a hazard. A typical homeowner's insurance policy provides coverage for fire (or loss from lightning) and wind damage (hailstorms, tornadoes, hurricane winds), but not storm surge. The protection against losses from earthquakes and floods requires additional policies and some hazards such as landslides are not covered at all (Kunreuther 1998). As a result, losses from hurricane winds are much higher in NATHAN ($345 billion) than in the other two databases.

Direct as well as insured losses capture only a fraction of the costs and impact of natural hazards. Indirect losses and uninsured losses, which if included would inflate monetary loss estimates dramatically (Heinz Center 1999). There are also nonmonetary losses. The utilization of accounts of nonmonetary losses, such as fatalities and injuries, however, is severely hampered by a lack of documentation. Hazard-related fatalities are underreported due to incomplete information on death certificates (Mathers et al. 2005; Smith Sehdev and Hutchins 2001; Thacker et al. 2008), and there is no systematic way to account for injuries. Thus, fatalities and injuries along with indirect losses and uninsured losses have yet to be fully accounted for in the estimation of losses from natural hazards.

Geographic bias. Changes in political geography also affect how hazard loss data are reported over space and time. Boundary changes at the country or subcountry level introduce spatial inconsistencies in the assignment of losses. Most databases report event losses according to the political geography at the time of the event. When undertaking a longitudinal study of hazard losses, it is crucial to account for boundary changes that might affect the spatial accuracy of loss data. Failure to do so results in excluding or double-counting loss information.

Political boundary changes and their effects on hazard loss data create problems at multiple spatial scales. To obtain all disasters from 1900 to 2007 that occurred in, for instance, the physical space now occupied by Croatia, one has to include information prior to June 1991 from Yugoslavia's disaster profile. Because the former Yugoslavia was larger than Croatia in its geographic extent, issues of spatial (dis)aggregation emerge. Using the same example, a user would have to employ some type of spatial or statistical interpolation to estimate how much of the former Yugoslavia's disaster profile could be attributed to the present-day Croatia if information from the entire 1900–2007 period of record is necessary for analysis.

The problems associated with changing geographies are also apparent at finer spatial scales. At a subnational scale, U.S. county boundary changes over time affect the SHELDUS database in much the same way national-level boundary changes impact EM-DAT or NATHAN. Rather than informing data users of this issue when downloading data from applicable geographic units, SHELDUS's smart query is sensitive to geographical changes and changes in naming conventions, and instantly attaches additional relevant loss records. A user querying the database for Miami-Dade County from 1960 through 2005 receives loss estimates for Dade County from 1960 to 1999 as well as loss estimates for Miami-Dade from 2000 onward.

Still, SHELDUS as well as Storm Events are not entirely free of a geographic bias. Here, the geographic bias is not a product of thresholds or changes in political boundaries, but a product of differences in reporting geography. This issue is most apparent during 1995 when the NWS changed its reporting strategy, moving from loss estimates by climate region to loss estimates in the specific counties where the event occurred. We speculate that states, which immediately switched to the new reporting procedure, potentially appear with higher frequency and presumably higher loss tallies in both SHELDUS and Storm Events in 1995. By 1996, every state followed the new reporting guidelines and provided specific loss estimates by county, which should have eliminated any geographic bias.

Systemic bias. Systemic bias between (and within) hazard loss reporting agencies underpin all the inherent problems with hazard loss data. These systemic biases arise from initial data collection and compilation, including how losses are computed and the source of the information. A good example of a systemic bias is the reporting in actual dollar losses versus inflation-adjusted losses or reporting in whole dollars versus loss categories. The NWS's former method of reporting losses in logarithmic categories, for instance, makes it extremely difficult to compare Storm Events estimates to other databases, such as SHELDUS (which used the lower boundary of Storm Event's logarithmic categories). Figure 2 illustrates hypothetical estimates loss for Storm Events when using the midpoint (mid) or upper boundaries (max) of logarithmic categories. The graphic shows that both Storm Events projections exceed the estimates of EM-DAT, NATHAN, and SHELDUS across the entire time period. In 1993, the maximum projection for the cumulative losses of the Midwest floods, southeastern drought, and "Storm of the Century" top more than \$160 billion in direct losses. Even though these midpoint and maximum estimates for Storm Events seem excessive, they represent a way to operationalize logarithmic loss categories. In fact, the *Extreme Weather Sourcebook* by the National Center for Atmospheric Research (NCAR) uses geometric means (slightly lower than midpoint estimates) to translate the Storm Data logarithmic categories into tornado loss estimates (NCAR 2008). This produces tornado loss estimates that are almost double the estimate of SHELDUS (\$47.3 billion in 2005 dollars for tornadoes from 1950 through 2006 for NCAR versus \$27.1 billion in 2005 dollars for events from 1950 through 2006 for SHELDUS). Which one is more accurate?

Another systemic bias stems from the treatment of multiple estimates for a unique event. Which estimate should be included into the database when there are different loss estimates for the same event? This is fairly straightforward in the case of Storm Events since it uses only one input source: loss estimates generated by NWS officials. EM-DAT, NATHAN, and SHELDUS on the other hand rely on secondary data from multiple sources. EM-DAT and NATHAN do not specify what steps are taken to resolve discrepancies between varying estimates. While NATHAN reports only insured losses collected from affiliated insurers, media, and so forth (Table 1), the losses reported by EM-DAT are an indistinguishable mix of direct and indirect losses. Furthermore, EM-DAT does not specify the data source for its estimates, which makes loss verification extremely difficult in EM-DAT (Vranes and Pielke 2009). In contrast, SHELDUS has a clearly defined policy and always uses the lowest estimate available when there is conflicting information from multiple sources. This explains why SHELDUS reports much lower total losses for the United States from 1960 through 2005 than both EM-DAT and NATHAN (Table 2).

IMPLICATIONS. Every disaster loss database is fraught with inconsistencies and suffers biases. One problem that binds all of them together is the lack of standard methods for collecting and reporting disaster loss data by international, federal, state, and local agencies. At first glance, these issues may appear to be mere technicalities, but these biases can be amplified and converted into fallacies by careless use of loss data. When risk assessments and the allocation of resources are based on such loss estimates, the outcome can be inadvertently flawed by the propagation of systemic and other biases inherent in databases such as those found in EM-DAT, NATHAN, SHELDUS, and Storm Events.

A widely referenced product that relies on uncertain loss estimates is the NCDC's estimate of billion dollar U.S. weather disasters (NCDC 2008a). The billion dollar weather disaster data are one of NCDC's most popular products and often referenced by the

TABLE 2. Selected U.S. losses according to different databases.

	EM-DAT			NATHAN			SHELDUS		
	1981–2000		1960–2005	1981–2000		1960–2005	1981–2000		1960–2005
	USD*	%	%	USD*	%	%	USD*	%	%
Droughts	8.8	5	3	28.9	10	7	17.9	13	9
Floods	52.4	30	34	45.6	16	14	46.4	34	28
Hurricanes/tropical storms	85.5	48	53	140.1	49	63	32.1	24	42
Landslides	1.3	1	1	—	—	<1	2.4	2	2
Volcanoes	—	—	<1	—	—	<1	0.3	<1	2
Earthquakes	29.6	17	8	74.3	26	14	36.8	27	17
Total	177.6	100	100	288.9	100	100	135.9	100	100

* 2005 billions.

media (Lott and Ross 2006). Rather than relying on internal NWS data (*Storm Data*), the authors of billion dollar weather disasters consult with state emergency management agencies, the Insurance Information Institute, U.S. government agencies, state and regional climate centers, and news media to gather loss estimates (Lott and Ross 2006). While laudable and a first step toward full-cost accounting, the merging of direct, indirect, insured, and insured losses into an indistinguishably mix of "total" losses eliminates the possibility of verifying losses. It also undermines the transparency of loss estimates, and is counterproductive to understanding the relationship between the various types of losses or improving data collection procedures. Ultimately, billion dollar weather disasters is a quick fix for media and politicians given that there are no better official estimates on the impact of natural hazards on society. The most recent example of the lack of reliable, official loss figures is the reliance of the U.S. Climate Change Science Program on loss figures from SHELDUS for billion dollar disasters instead of government agencies (CCSP 2008).

CONCLUSIONS. Current global and national databases for monitoring losses from national hazards suffer from a number of limitations, which in turn lead to misinterpretation hazard loss data. These biases include 1) hazard bias, which produces an uneven representation and distribution of losses between hazard types; 2) temporal bias, which makes it difficult to compare losses across time due to less reliable loss data in past decades; 3) threshold bias, which results in an underrepresentation of minor and chronic events; 4) accounting bias, which underreports indirect, uninsured, and others losses; 5) geographic bias, which generates a spatially distorted picture of losses by over- or underrepresented certain locales; and 6) systemic bias, which makes it difficult to compare losses between databases due to different estimation and reporting techniques.

To overcome these problems and to provide high quality loss data to planners, decision makers, the public, and other end users, we recommend standardizing some key areas such as loss data collection, documentation, accessibility, and dissemination. Clear guidelines and standard procedures must be developed on how to estimate losses for all types of natural hazards coordinated and implemented across the various federal agencies in charge of collecting hazard event and loss data. Common naming conventions for similar phenomena and assigning unique identifiers to an event would streamline interagency record keeping and reduce the likelihood that a user looking for data on a particular hazard misses a source because they searched for their hazard of choice under a different name.

The proprietary nature of some loss databases mostly held by insurance and reinsurance companies restricts analytical studies and our understanding regarding the spatial and temporal distribution of insured losses. Some researchers have therefore called for peer-reviewed, open-source databases (Bouwer et al. 2007), while others have called upon agencies such as the National Oceanic and Atmospheric Administration (NOAA) and USGS to play a more vital role (Cutter et al. 2008). However, without full integration of standard methods between loss data producers as well as loss databases, disaster data will continue to lack comparability, limiting users' abilities to draw meaningful conclusions about the nature of disaster losses over time and across spatial scales.

So, what are the true direct losses of natural hazards since 1960? And more importantly, what are the true societal (or hidden) costs of natural hazards in the United States since 1960? Based on the loss figures presented in this paper, it appears that—at least in the United States—insured losses (see NATHAN) exceed direct losses (see SHELDUS). Since not every person or home or business is insured, we would expect to find the opposite relationship with direct losses surpassing insured losses. However, loss tallies by SHELDUS and Storm Events are far below insured losses. This seems to suggest that either a) the assumption about the relationship between direct and insured losses is incorrect, or b) direct loss estimates are incomplete and the nation has suffered much higher direct losses from natural hazards than currently documented.

Achieving resilient and sustainable communities (SDR 2005) requires systematic and comprehensive inventories at the national as well as international level. The time is now upon us to establish the much needed and long overdue National Inventory of Hazard Events and Losses, an open access comprehensive data clearinghouse for natural hazard loss information. The policy imperative is clear: how can we reduce losses from natural hazards when we do not know how such losses are counted and when and where they occur?

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