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Power Distribution and Probabilistic Forecasting of Economic Loss and Fatalities due to Hurricanes, Earthquakes, Tornadoes, and Floods in the United States

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POWER DISTRIBUTION AND PROBABILISTIC FORECASTING OF ECONOMIC LOSS AND FATALITIES DUE TO HURRICANES, EARTHQUAKES, TORNADOES, AND FLOODS IN THE UNITED STATES

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By

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I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Scott Edward Baker ENTITLED Power Distribution and Probabilistic Forecasting of Economic Loss and Fatalities Due to Hurricanes, Earthquakes, Tornadoes, and Floods in the United States BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science.

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ABSTRACT

Baker, Scott Edward. M.S. Department of Earth and Environmental Sciences, Wright State University, 2016. Power Distribution and Probabilistic Forecasting of Economic Loss and Fatalities Due to Hurricanes, Earthquakes, Tornadoes, and Floods in the United States.

Traditionally, the size of natural disaster events such as hurricanes, earthquakes, tornadoes, and floods is measured in terms of wind speed (m/sec), energy released (ergs), or discharge (m^3/sec). Economic loss and fatalities from natural disasters result from the intersection of the human infrastructure and population with the natural event. This study investigates the size versus cumulative number distribution of individual natural disaster events in the United States. Economic losses are adjusted for inflation to 2014 United States Dollars (USD). The cumulative number divided by the time over which the data ranges is the basis for making probabilistic forecasts in terms of the Number of Events Greater Than a Given Size Per Year and it's inverse, Return Period. Such forecasts are of interest to insurers/re-insurers, meteorologists, seismologists, government planners, and response agencies.

Plots of size versus cumulative number distributions per year for economic loss and fatalities are well fit by power scaling functions of the form $P(x) = Cx^{-\beta}$; where, P(x) is the cumulative number of events per year with size equal to and greater than size x (or probability of occurrence), C is a constant which measures the activity level, x is the

event size, and β is the scaling exponent. Power distributions have a property referred to as self-similar or scale free, so that any sample of the distribution at any scale is statistically identical to the whole distribution.

Economic loss and fatalities due to hurricanes, earthquakes, tornadoes, and floods are well fit by power functions over one to five orders of magnitude in size. Economic losses for hurricanes and tornadoes have greater scaling exponents, $\beta = 1.1$ and 0.9 respectively, whereas earthquakes and floods have smaller scaling exponents, $\beta = 0.4$ and 0.6 respectively. The value of the scaling exponent determines the petitioning of losses between larger and smaller sized events. All of the data sets exhibit a roll-off for smaller economic loss events. The roll-off below a certain size is attributed to either under estimating the economic losses or to a transition away from a power function below which the cumulative number is independent of size. Fatalities for tornadoes and floods have greater scaling exponents, $\beta = 1.5$ and 1.7 respectively, whereas hurricanes and earthquakes have smaller scaling exponents, $\beta = 0.4$ and 0.7 respectively.

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CHAPTER 1

INTRODUCTION

1.1 Purpose of Study

Natural disasters in the United States are of concern to national and regional planners, the insurance industry, and the emergency response community because of the associated economic losses and fatalities. Traditionally, the size of a natural disaster is measured in terms of wind speed (m/sec) for hurricanes and tornadoes, energy released (ergs) for earthquakes, and discharge (m^3/sec) for floods.

Economic loss and fatalities from natural disasters result from the intersection of the human infrastructure and population with the natural event. An important purpose of this study is to determine whether economic loss and fatalities can be fit by a mathematical distribution. This study investigates economic loss and fatalities due to four natural disaster types (hurricanes, earthquakes, tornadoes, and floods) in the United States for various windows of time.

1.2 Previous Studies

Identifying a mathematical function permits forecasting the probability of an event of a given size and greater, during a given time window. This approach was developed and applied in two previous studies where economic loss and fatality data were used as measures of event size for natural disasters by Barton and Nishenko, 1994 and Nishenko and Barton, 1996. These two studies were the first to show that economic losses and fatalities due to natural disasters are well fit by a power function. Their work provides the basis for the present study in which the outcome and analysis of newer, more complete data sets of the present study can be compared.

Barton and Nishenko (1994) developed a method to forecast economic losses and fatalities for natural disasters using power functions and their scaling exponents. Plotting size versus cumulative number, they found that for hurricanes and earthquakes, individual event sizes are well fit by a power function over one and a quarter to three and a half (1.25-3.5) orders of magnitude in size for economic losses (Figure 1.1 (page 4) and Table 1.1 (page 6)). Plotting size versus cumulative number, they found that for hurricanes, earthquakes, tornadoes, and floods, individual event sizes are well fit by a power function over one to three and a quarter (1-3.25) orders of magnitude in size for fatalities (Figure 1.2 (page 5)). Note that they reported economic loss distributions only for hurricanes and earthquakes with scaling exponents, $\beta = 1.0$ and 0.4 respectively (Figure 1.1 and Table 1.1).

Nishenko and Barton (1996) studied size versus cumulative number distributions for fatalities due to earthquakes at locations around the world and compared the power function scaling exponents, $\beta = 0.2$-0.5. For Asia, Europe, and South America, the data was well fit by a power function. For the Middle East, the data rolled off from a power function at both larger and smaller losses. A roll-off of the data for larger losses and a roll-off of the data to a slope of zero for the smallest sizes were not addressed. Nishenko and Barton (1996) also showed fatalities distributions for hurricanes, earthquakes, tornadoes, and floods in the United States (see Figure 1.2 (page 5) and Table 1.1 (page 6)). In addition to demonstrating power function behavior over one to three and a quarter

(1-3.25) orders of magnitude in size, the scaling exponents form two groups. Hurricanes and earthquakes are associated with smaller scaling exponents, $\beta = 0.6$ and 0.4 respectively, while tornadoes and floods have greater scaling exponents, $\beta = 1.4$ and 1.3 respectively. The results of these two previous studies are summarized in Table 1.1.

Table 1.2 (page 7), reproduced from Barton and Nishenko (1994), presents probability estimates of an event of a given size and greater in any given year for 10 and 1000 fatality events for each disaster type. It also provides a return period (inverse of the probability of occurrence in any given year) based on the power functions shown on Figure 1.2 (page 5). The return period is an estimate of the likelihood of an event based on historical data collected, not its periodic recurrence. They noted that floods and tornadoes have relatively shorter return periods for small events, while earthquakes and hurricanes have relatively short return periods for large events.

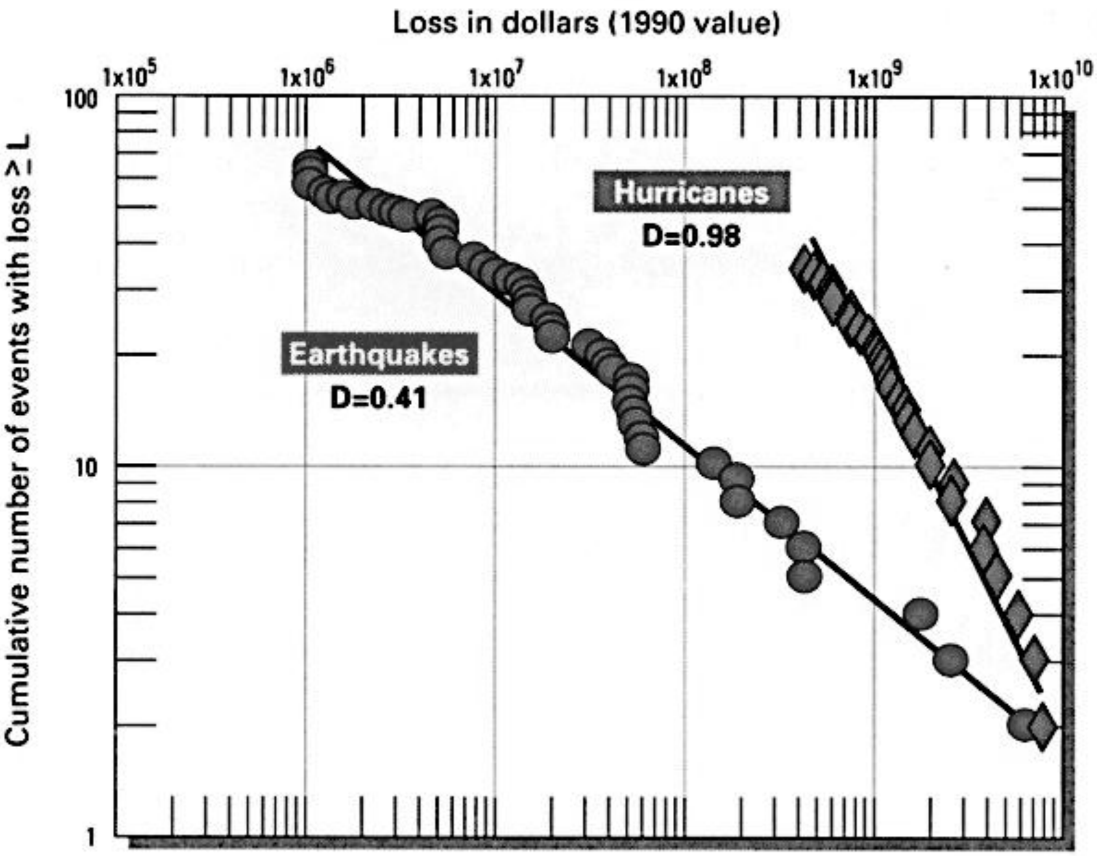


Figure 1.1. Plot of cumulative frequency of economic loss (in 1990 USD) due to earthquakes and hurricanes in the United States between 1900 and 1989. Data plotted as loss size (x-axis) versus cumulative number of events (y-axis) are well fit by power functions with scaling exponents for earthquakes = 0.4 and hurricanes = 1.0. Note, each point on the plot represents a single event. Number of data points for earthquakes = 49 and for hurricanes = 27. (Barton and Nishenko, 1994).

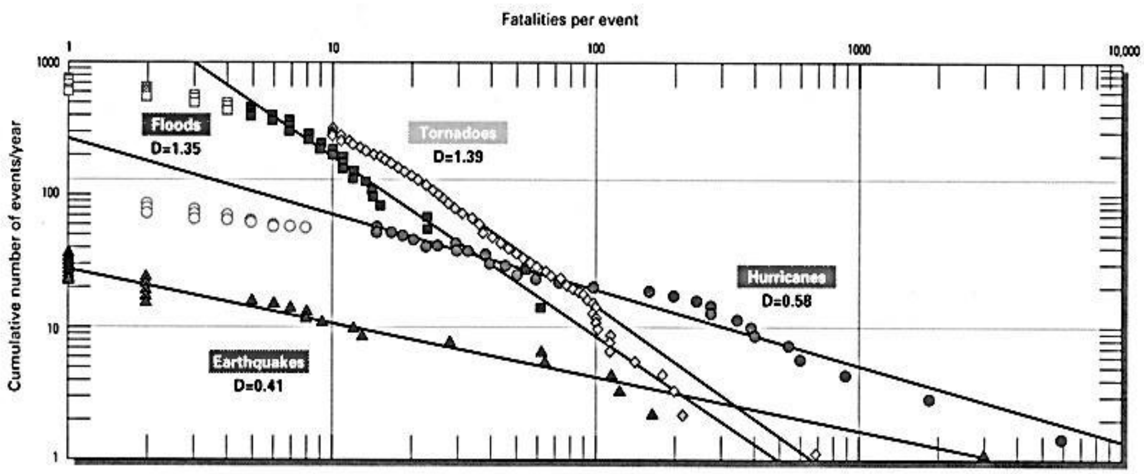


Figure 1.2. Plot of cumulative frequency of life loss due to earthquakes, hurricanes, tornadoes, and floods in the United States between 1900 and 1989. Data plotted as fatality size (x-axis) versus cumulative number of events per year (y-axis) are well fit by power functions with scaling exponents of 0.4 for earthquakes, 0.6 for hurricanes, 1.4 for tornadoes, and 1.3 for floods. Note, each point on the plot represents a single event. Number of data points used to fit power function for earthquakes = 28, hurricanes = 30, tornadoes = 56, and floods = 28. Power functions range from one to three and a half orders of size in X; the scaling exponents form two groups. Hurricanes and earthquakes are associated with relatively flat slopes (0.4-0.6); while tornadoes and floods have steeper slopes (1.3-1.4). Open symbols were not used in fitting power functions. (Barton and Nishenko, 1994).

Table 1.1. Data and results previous study by Barton and Nishenko (1994). Event type, data source, date range, total number of events, number of economic loss events, number of fatality events, range of economic losses (1990 USD), range of fatalities, number of economic loss events fit by power function, number of fatality events fit by power function, economic loss scaling exponent, β, and fatalities scaling exponent, β.

EVENT TYPE	DATA SOURCE	DATE RANGE	TOTAL # OF INDIVIDUAL EVENTS	# OF ECONOMIC LOSS EVENTS	# OF FATALITY EVENTS	RANGE OF ECONOMIC LOSSES (1990 USD) (Orders of Magnitude in Size)	RANGE OF FATALITIES (Orders of Magnitude in Size)	# OF ECONOMIC LOSS EVENTS FITTED	# OF FATALITY EVENTS FITTED	ECONOMIC LOSS β VALUE	FATALITIES β VALUE
HURRICANE	NOAA	1900-1989	44	27	44	$400,000,000-$8,000,000,000 (~1.25 Orders)	1-5,900 (~2.5 Orders)	27	30	1.0	0.6
EARTHQUAKE	US DEPARTMENT OF COMMERCE	1900-1989	49	49	28	$1,000,000-$6,000,000,000 (~3.5 Orders)	1-3,000 (~3.25 Orders)	49	28	0.4	0.4
TORNADO	NOAA	1900-1989	56	-----	56	-----	1-790 (~1.75 Orders)	-----	56	-----	1.4
FLOOD	UNITED STATES ARMY CORPS OF ENGINEERS	1900-1989	44	-----	44	-----	1-60 (~1 Order)	-----	28	-----	1.3

Table 1.2. Probability estimates for the occurrence of earthquake, hurricane, flood, and tornado disasters with 10 and 1000 fatalities per event in the United States during 1, 10, and 20 year exposure times, and estimates of the mean return periods in years. Note the reversal in recurrence times for small and large events. Tornadoes and floods have relatively short return periods for small events, while hurricanes and earthquakes have relatively short return periods for large events. (Barton and Nishenko, 1994)

Exposure time / Disaster	10 fatalities per event			
	1 year	10 years	20 years	Return time (in years)
Earthquakes	0.11*	0.67	0.89	9
Hurricanes	0.39	0.99	>0.99	2
Floods	0.86	>0.99	>0.99	0.5
Tornadoes	0.96	>0.99	>0.99	0.3

* 0.11 = 11% probability of occurrence

Exposure time / Disaster	1000 fatalities per event			
	1 year	10 years	20 years	Return time (in years)
Earthquakes	0.01	0.14	0.26	67
Hurricanes	0.06	0.46	0.71	16
Floods	0.004	0.04	0.08	250
Tornadoes	0.006	0.06	0.11	167

CHAPTER 2

DATA

2.1 Introduction

Economic loss and fatality data for natural disasters (hurricanes, earthquakes, tornadoes, and floods) in the United States are collated from public and private sources including: United States Geological Survey (USGS), National Oceanic and Atmospheric Administration (NOAA), and insurance companies. The data used in the present study were downloaded from the following websites: NOAA National Center for Environmental Information (NCEI) (earthquakes, tornadoes, and floods) and NOAA National Hurricane Center (NHC) (hurricanes). The data are collated and presented online, but are not edited by NOAA (https://www.ncdc.noaa.gov/stormevents/faq.jsp). As part of the present study, the value of economic losses was adjusted to 2014 USD using the Bureau of Labor Statistics Consumer Price Index Inflation Calculator (http://www.bls.gov/data/inflation_calculator.htm).

2.2 Sources, Time and Value Ranges of Data

The data used in this study are collated on the NOAA National Center for Environmental Information webpage (https://www.ncei.noaa.gov/), but are generated by several federal agencies. Tornado and flood data were generated by NOAA National Weather Service (http://www.weather.gov/), hurricane data were generated by NOAA

National Hurricane Center (http://www.nhc.noaa.gov/), and earthquake data were generated by United States Geological Survey and collated by NOAA National Geophysical Data Center (https://www.ngdc.noaa.gov/). A data summary for each natural disaster type is presented below and in Table 2.1 (page 13). Procedures used to process the data, to group it into events, and to prepare it for analysis are given in Appendix A.

2.2.1 Hurricane Data Source

Hurricane data used in the present study were downloaded from NOAA National Hurricane Center Tropical Cyclone Reports (http://www.nhc.noaa.gov/data/#tcr). As shown in Table 2.1, the data ranges in time from 1950 to 2014, with 94 individual events. Of the 94 individual events, 92 have reported economic losses ranging from \$610,500 to \$130,680,000,000 (2014 USD). Of the 94 individual events, 82 have reported fatalities ranging from 1 to 1,833. In the present study, unreported losses are not interpreted to equal zero or any other value. The data are listed in the source by event. The data were assembled by NOAA National Hurricane Center, and incorporate insurance company data. A second data set was assembled by the NOAA National Weather Service and collated by NOAA National Center for Environmental Information (NCEI) (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/). This second data set was incomplete and was used in the present study to investigate the consistency in loss data for hurricanes and by extrapolation, other loss data sets.

2.2.2 Earthquake Data Source

Earthquake data used in the present study were downloaded from NOAA National Center for Environmental Information Significant Earthquake Database (http://ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1) (formerly NOAA National Geophysical Data Center). As shown in Table 2.1, the data ranges in time from 1900 to 2014, with 196 individual events. Of the 196 individual events, 144 have reported economic losses ranging from $75,200 to $64,000,000,000 (2014 USD). Of the 196 individual events, 58 have reported fatalities ranging from 1 to 700. In the present study, unreported losses are not interpreted to equal zero or any other value. The data are listed by event. The data were assembled by the United States Geologic Survey and collated by NOAA National Center for Environmental Information (http://www.ngdc.noaa.gov/hazard/earthqk.shtml).

2.2.3 Tornado Data Source

Tornado data used in the present study were downloaded from NOAA National Center for Environmental Information Storm Events Database (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/) (formerly NOAA National Climatic Data Center). As shown in Table 2.1, the data set ranges in time from 1950 to 2014, with 46,402 individual events. Of the 46,402 individual events, 31,567 have reported economic losses ranging from $14.70 to $2,217,500,000 (2014 USD). Of the 46,402 individual events, 1,282 have reported fatalities ranging from 1 to 116. In the present study, unreported losses are not interpreted to equal zero or any other value. The data are listed by event. The data for each event were assembled by NOAA National Weather Service County Warning Area (CWA) offices (Figure 2.1 (page 11)) and then collated by NOAA National Center for Environmental Information (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/).

Figure 2.1: NOAA National Weather Service County Warning Area (CWA) map. This map shows the location of the 122 NWS filed offices throughout the country. Each label represents the city location of the office within the CWA. (http://innovation.srh.noaa.gov/you/officemap.php)

2.2.4 Flood Data Source

Flood data (including: floods, flash floods, marine floods, and coastal floods) used in the present study were downloaded from NOAA National Center for Environmental Information Storm Events Database (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/) (formerly NOAA National Climatic Data Center). As shown in Table 2.1, the data set ranges in time from 1996 to 2014, with 6,230 individual events. Of the 6,230 individual events, 4,131 have reported economic losses ranging from $11.70 to $134,925,353,120 (2014 USD). Of the 6,230 individual events, 601 have reported fatalities ranging from 1 to 38. In the present study, unreported losses are not interpreted to equal zero or any other value. The data for each event was collected by NOAA National Weather Service CWA offices and collated by NOAA National Center for Environmental Information (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/).

2.2.5 Combining Flood Data into Events

The hurricane, earthquake, and tornado data are presented as individual events in the online NOAA databases. Flood data are not combined into individual events and this task was done as part of the present study.

The NOAA National Weather Service is made up of 122 offices (Figure 2.1 (page 11)) around the United States and surrounding territories. These offices use storm damage surveys (Appendix D) to estimate economic losses; while a majority of economic loss and fatality data are reported by state and other federal agencies, public media, and insurance companies (https://www.ncdc.noaa.gov/stormevents/faq.jsp). Compiling information from these sources, by NOAA employees, provides the data in the NOAA data sets. Economic loss and fatality data collected by NOAA National Weather Service CWA's are input into NOAA National Center for Environmental Information Storm Events Database by the NOAA NWS CWA, and then aggregated at the state level. Each event that crosses a CWA boundary is reported once for each county affected, with a beginning and ending location. NOAA NWS CWA offices report loss numbers by county (https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf, 76 & 81-83).

Table 2.1. Data Summary: event type, source of data, date range, number of individual events, number of economic loss events, range of economic loss (adjusted to 2014USD), number of fatality events, and range of fatalities for United States hurricanes, earthquakes, tornadoes, and floods.

EVENT TYPE	**DATA SOURCE**	**DATE RANGE**	**TOTAL # OF INDIVIDUAL EVENTS**	**# OF ECONOMIC LOSS EVENTS**	**# OF FATALITY EVENTS**	**RANGE OF ECONOMIC LOSSES (2014 USD)** **(Orders of Manitude in Size)**	**RANGE OF FATALITIES** **(Orders of Manitude in Size)**
HURRICANE	NOAA NATIONAL HURRICANE CENTER TROPICAL CYCLONE REPORTS	1950-2014	94	92	82	\$610,500-\$130,680,000,000 (~5.5 Orders)	1-1,833 (~3.2 Orders)
EARTHQUAKE	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1900-2014	196	144	58	\$75,200-\$64,000,000,000 (~6.0 Orders)	1-700 (~2.75 Orders)
TORNADO	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1950-2014	46,402	31,567	1,282	\$14.70-\$2,217,500,000 (~8.0 Orders)	1-116 (~2.0 Orders)
FLOOD	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1996-2014	6,230	4,131	601	\$11.70-\$134,925,353,120 (~10.0 Orders)	1-38 (~1.5 Orders)

2.3 Preparation of the Data Before Analysis

Step-by-step directions for downloading the economic loss and fatality data sets from the NOAA National Center for Environmental Information website in comma delimited files and reconfiguring into Excel files for grouping the data into events using a Matlab code are given in Appendix A.

2.3.1 Hurricanes

For hurricanes, the economic loss and fatality values in the database (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/) did not agree with those in the NOAA National Hurricane Center Tropical Cyclone Reports (http://www.nhc.noaa.gov/data/#tcr). Fatality values varied based on indirect and direct fatalities associated with each natural disaster. The present study summed all fatalities (indirect and direct) from an event and incorporated them into the total value. Economic loss values did not agree due to adjustments after the event occurred, as well as NOAA National Weather Service CWA’s improperly reporting events. NOAA NHC Tropical Cyclone Reports were extensively detailed, so they will be used for this study.

2.3.2 Earthquakes

Earthquake economic loss and fatality data for individual events often cited a range of values (ex. $50-$500, or 1-10 fatalities). In the present study, the mean of the range was the value used for analysis.

2.3.3 Tornadoes

Tornado data were already sorted into individual events.

2.3.4 Floods

Flood data in the NOAA database (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/) were compiled by NOAA National Weather Service, and then grouped by state, which makes grouping by event a labor-intensive process. For the present study, Federal Emergency Management Agencies Disaster Declarations webpage (https://www.fema.gov/disasters) was used to group the data into individual events. The Disaster Declarations pages were used to establish the time frame and location of each event, which were then combined to form an event.

2.4 Errors in the Data

Economic loss and fatality data used in this study contain errors. Error originates from the incomplete and erroneous collection of data. "The Storm Events Database is an official publication of the National Oceanic and Atmospheric Administration (NOAA) which documents the occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce. When information included in Storm Data originates from a source outside the NWS, such as insurance losses included in the present study, the source is cited. The data are collected using the best available information, but data values are unverified by NOAA due to time and resource constraints," (https://www.ncdc.noaa.gov/stormevents/faq.jsp). A National Weather Service Directive (https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf, pp. 9-13) details how economic losses and fatalities can be estimated if true values cannot be obtained. "CWA meteorologists are allotted sixty days to gather data from sources for each event. Additions and corrections to the data turned in within the first sixty days may be made at a later time, up to several years after the event," (Stuart Hinson, NCDC, personal communication). NWS Directives Appendix B gives CWA meteorologists a range of values for objects frequently damaged during events. CWA meteorologists have significant latitude in what they choose to report. This introduces an unknown error into each loss value listed in the NOAA data sets. Therefore, no errors are reported for any of the economic loss and fatality values analyzed in the present study.

2.4.1 Sources of Errors in Hurricane Data

NOAA National Weather Service CWA offices label many concurrent events with a different identifier number. For example, Hurricane Katrina impacted three National Weather Service CWA offices serving Louisiana: New Orleans, Lake Charles, and Jackson (see Figure 2.1 (page 11)). These three offices labeled this event with three different episode identifiers of 197919, 196079, and 196783 respectively. Summing the economic losses and fatalities reported by each office with the Baker Event ID Number (Appendix C Table C.1 (page 90)), did not result in economic loss and fatality values reported in the NOAA National Hurricane Center Tropical Cyclone Report (http://www.nhc.noaa.gov/data/tcr/AL122005_Katrina.pdf). The NOAA National Hurricane Center Tropical Cyclone Reports are detailed. The NOAA NCEI database was initiated in 1996, and previous events are not included. Losses and fatalities for events prior to 1996 are contained in the Tropical Cyclone Reports of NOAA National Hurricane Center's Data Archive (http://www.nhc.noaa.gov/data/#tcr), which extends back to 1950. As shown in Table 2.1 (page 13), this data set also included 2 events for which no economic losses are reported and 12 events for which no fatalities are reported. The present study does not interpret a lack of economic loss or fatality values to mean 0, or a value greater than 0.

2.4.2 Sources of Errors in Earthquake Data

The earthquake data set had errors associated with both economic loss and fatalities, previously listed in Section 2.3. As shown in Table 2.1, this data set also included 52 events for which no economic losses are reported and 138 events for which no fatalities are reported. The present study does not interpret a lack of economic loss or fatality values to mean 0, or a value greater than 0.

2.4.3 Sources of Errors in Tornado Data

NOAA National Weather Service CWA offices conduct tornado damage surveys as well as gather data from other institutions, not limited to governmental facilities. Another source is when tornado paths overlap, causing economic loss and fatality values to be incorrectly assigned. As shown in Table 2.1, this data set also included 14,835 events for which no economic losses are reported and 45,120 events for which no fatalities are reported. The present study does not interpret a lack of economic loss or fatality values to mean 0, or a value greater than 0.

2.4.4 Sources of Errors in Flood Data

Floods were not combined into events in the NOAA database. Combining episode data by date and state identified events. As shown in Table 2.1, this data set also included 2,099 events for which no economic losses are reported and 5,629 events for which no fatalities are reported. The present study does not interpret a lack of economic loss or fatality values to mean 0, or a value greater than 0.

2.4.5 Estimating Errors

NOAA provides no estimate of error for any of the economic loss or fatality data. Since the true value of these losses is not known, it is not possible to calculate or even estimate an error for the economic loss or fatality data used in the present study. However, consistency of the values can be quantified where there are two values of losses for the same event. There are two databases for losses due to hurricanes. The difference in the economic loss and fatality data, between the NOAA National Center for Environmental Information Storm Events Database (ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/) and the NOAA National Hurricane Center Tropical Cyclone Reports (http://www.nhc.noaa.gov/data/#tcr). The difference in loss values is a measure of consistency between data sets and is used to quantify consistency. Table 2.2 (page 19) lists the economic loss and fatalities for thirty-two hurricane events. Without two data sets, it is not possible to quantify consistency for earthquakes, tornadoes, and floods. Consistency of the hurricane data is calculated by taking the absolute value of the difference in economic loss or fatalities between the two data sets. Figures 2.2 (page 20) and 2.3 (page 21) present a graphical representation of the consistency of economic loss and fatalities respectively.

Table 2.2: Differences in hurricane economic loss and fatality reporting. Data includes: event date, NOAA NCEI database economic loss (2014 USD), NOAA NHC economic loss (2014 USD), difference in economic loss (2014 USD), NOAA NCEI fatalities, NOAA NHC fatalities, and difference in fatalities.

EVENT DATE	ECONOMIC LOSS (2014 USD)		ECONOMIC LOSS DIFFERENCE (2014 USD)	FATALITIES		FATALITIES DIFFERENCE
	NOAA NCEI	NOAA NHC REPORTS		NOAA NCEI	NOAA NHC REPORTS	
07/1996	$474,404,250	$407,700,000	$66,704,250	3	7	4
09/1996	$1,885,914,500	$4,832,000,000	$2,946,085,500	14	34	20
07/1997	$99,960,000	$99,960,000	$0	1	9	8
08/1998	$521,360,550	$1,044,000,000	$522,639,450	1	3	2
09/1998	$10,624,150	$114,550,000	$103,925,850	2	3	1
09/1998	$1,958,151,050	$8,700,000,000	$6,741,848,950	1	1	0
08/1999	$4,454,540	$0	$4,454,540	0	0	0
09/1999	$6,570,127,000	$9,798,000,000	$3,227,873,000	14	56	42
10/1999	$926,231,920	$1,136,000,000	$209,768,080	1	8	7
09/2000	$6,918,500	$0	$6,918,500	0	0	0
11/2001	$67,000	$0	$67,000	0	0	0
10/2002	$907,305,313	$1,221,000,000	$313,694,687	0	2	2
07/2003	$14,035,587	$232,200,000	$218,164,413	0	3	3
09/2003	$1,295,886,270	$6,927,300,000	$5,631,413,730	6	50	44
08/2004	$7,239,518,750	$18,891,250,000	$11,651,731,250	9	35	26
08/2004	$0	$162,500,000	$162,500,000	0	9	9
08/2004	$9,437,500	$9,437,500	$0	0	1	1
09/2004	$7,042,775,000	$11,883,750,000	$4,840,975,000	0	48	48
09/2004	$8,335,582,250	$23,525,000,000	$15,189,417,750	14	57	43
09/2004	$927,006,250	$9,575,000,000	$8,647,993,750	0	4	4
07/2005	$2,118,649,500	$3,466,650,000	$1,348,000,500	2	16	14
08/2005	$40,545,563,300	$130,680,000,000	$90,134,436,700	21	1,833	1,812
09/2005	$74,971,600	$84,700,000	$9,728,400	0	1	1
09/2005	$7,571,109,150	$14,564,770,000	$6,993,660,850	6	62	56
10/2005	$12,342,000,000	$25,418,470,000	$13,075,470,000	5	5	0
09/2007	$3,420,000	$3,420,000	$0	0	1	1
07/2008	$0	$1,155,000,000	$1,155,000,000	0	1	1
09/2008	$24,079,000	$5,079,800,000	$5,055,721,000	0	52	52
09/2008	$1,482,800,000	$32,472,000,000	$30,989,200,000	1	85	84
08/2011	$3,675,000	$16,590,000,000	$16,586,325,000	0	41	41
08/2012	$750,767,000	$4,052,000	$746,715,000	3	5	2
07/2014	$0	$4,052,000	$4,052,000	0	0	0

Figure 2.2 shows consistency for economic losses due to hurricanes in the United States over the time window, 1996-2014. The smaller time window used for comparison is due to the limitation of data through the NOAA NCEI database, dating back to 1996. The consistency of each event shows that the values of economic loss (2014 USD) follow a linear function, over time, in which the difference between the data sets increases at a rate equivalent to the increase in economic loss (2014 USD).

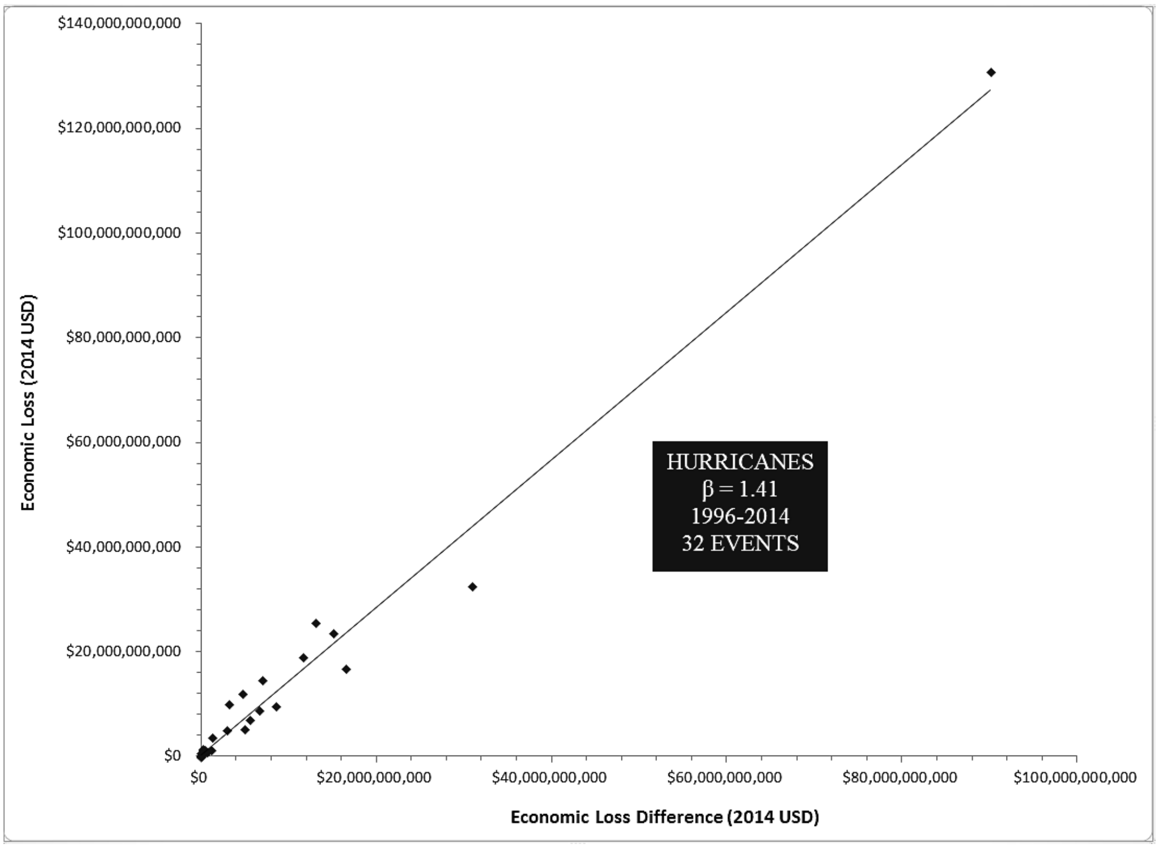


Figure 2.2. Economic loss consistency for United States hurricanes, 1996-2014. The x-axis is the economic loss difference (2014 USD) between the NOAA NCEI database and NOAA NHC Tropical Cyclone Reports. The y-axis is the larger economic loss value (2014 USD) of the two data sets used for comparison to estimate consistency between the data.

Figure 2.3 shows consistency for fatalities due to hurricanes in the United States over the time window, 1996-2014. The smaller time window used for comparison is due to the limitation of data through the NOAA NCEI database, dating back to 1996. The consistency of each event shows that the values of fatalities follow a linear function, over time, in which the difference between the data sets increases at a rate equivalent to the increase in fatalities.

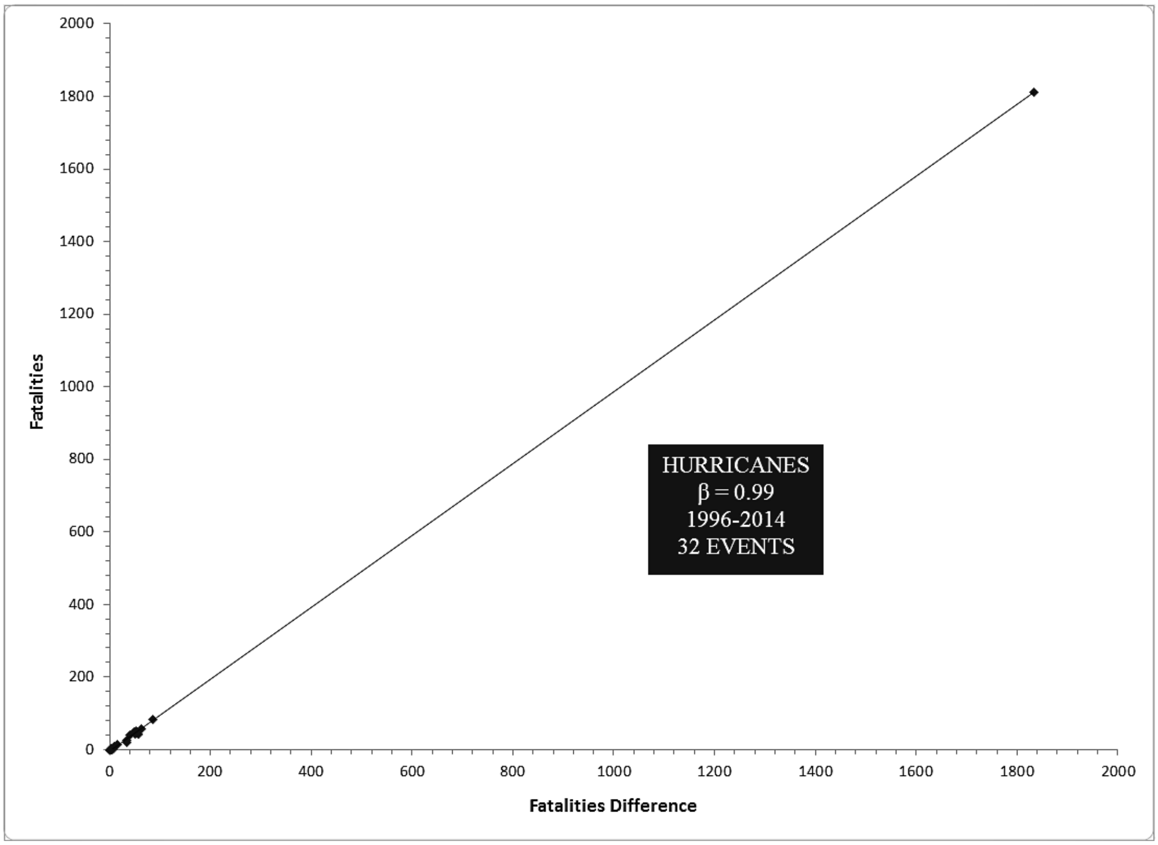


Figure 2.3. Fatalities consistency for United States hurricanes, 1996-2014. The x-axis is the fatalities difference between the NOAA NCEI database and NOAA NHC Tropical Cyclone Reports. The y-axis is the larger fatalities value of the two data sets used for comparison to estimate consistency between the data.

CHAPTER 3

ANALYSIS OF DATA

3.1 Method of Analysis

Barton and Nishenko (1994) and Nishenko and Barton (1996) pioneered the use of power functions to fit size-cumulative frequency plots of natural disaster economic losses and fatalities over one to four orders of magnitude in size (Figures 1.1 (page 4) and 1.2 (page 5)). Newman (2006) cites a wide variety of natural and non-natural disaster data sets for which cumulative frequency distributions and histograms follow a power function over multiple orders of magnitude in size (including: 1. earthquake magnitude, 2. word frequency in the novel *Moby Dick*, 3. citations of scientific papers published in 1981, and cited between publication and June 1997, 4. web hits received by web sites from users of AOL Internet, 5. population of US cities recorded by US Census Bureau in 2000, and others). These examples show that power function distributions are not limited to natural sciences, they can occur in physical, biological, technological, and social systems of various kinds (Newman, 2006).

The method of analysis used in the present study (following Barton and Nishenko, 1994, and Nishenko and Barton, 1996) is to plot the economic loss or fatality data for individual events on a size versus cumulative frequency plot with log-log axes and fitting the data (Figures 3.1-3.8 (pages 26-35)) with a power function of the form:

$$p(x) = Cx^{-\beta}$$

where:

$p(x)$ = cumulative number of events per year with size equal to and greater than size x (probability of occurrence)

C = a constant; measure of the activity level

β = the slope value of the power function fit to the data

The probability of the occurrence for an event of a given size and greater in any one year, left y-axis on the size-cumulative frequency plots (Figures 3.1-3.8), is calculated by dividing the cumulative number of events by the number of years spanned by the data set. The “return period” (in years) for any given event size and greater, is the inverse of the probability of occurrence and is shown on the right y-axis on each plot.

Economic losses less than ~$1 million for tornadoes and floods, ~$10 million for earthquakes, and ~$10 billion for hurricanes fall away from the power function fit to the larger events. The economic losses roll-off for values less than ~$100,000 for tornadoes and floods, and ~$100 million for hurricanes is attributed to either an under estimate of smaller sized events or to a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data can be fit by a power function with a scaling exponent of zero (a horizontal line). Hurricane data between 50 and 60 fatalities has a rapid increase in the number of events. Fatality data below ~5 for earthquakes fall away from the power function fit to the larger events. Tornado fatalities below 1 roll-off from the power function fit to larger events, and include a roll-off at an upper limit. Flood fatalities are well fit by a single power function over the entire distribution.

For purpose of comparison, the size-cumulative frequency plots also include the data plotted in histogram form, which is non-cumulative, with equally sized bin intervals (Burroughs and Tebbens, 2001, and Newman, 2006). The bin interval sizes used in Figures 3.1-3.8 (pages 26-35) are stated in the figure captions. The points shown in Figures 3.1-3.8 are the top right corners of the histogram bars. The data sets were too small and too scattered to permit the tops of the histogram bars to be meaningfully fit by any function or functions.

3.2 Results of Data Analysis

Figures 3.1-3.8 show cumulative number of events per year equal to and greater than size x (an event) for economic losses (odd numbered figures) and fatalities (even numbered figures). The x-axis is the size of individual events, the left y-axis is the number of events of a given size and greater divided by the time span of the data set, which is the probability of occurrence in any one year. The probability of the largest event is 1/(time span of the data set) and the probability of the second largest event and greater is 2/(time span of the data set) and so on for all of the event sizes in the data set. The right y-axis is the return period (in years) for an event of any given size and greater. As illustrated on Figures 3.1-3.8, where there are repetitive size values, only the greatest cumulative value is used for fitting a mathematical function to the data (Burroughs and Tebbens, 2001). Non-fit and repetitive values for economic loss and fatalities are shown on the plots in light gray, the black data points are fit by a power function.

3.2.1 Hurricanes

Figure 3.1 is a size-cumulative frequency plot for economic losses in the United States for individual hurricane events during the time window 1950-2014. Data greater than $7 billion are well fit by a power function over one and a quarter orders of magnitude in size. The roll-off below $100 million is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

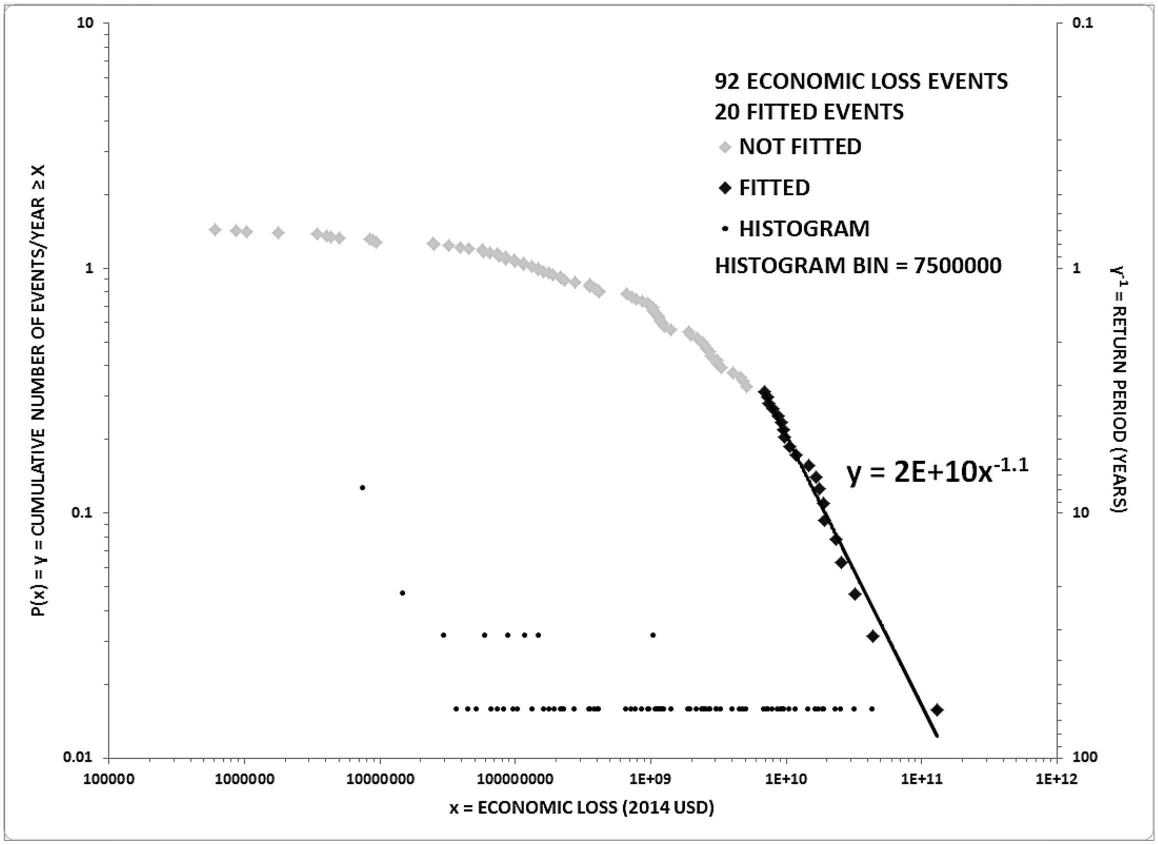


Figure 3.1. Size-cumulative frequency plot of hurricane economic losses for 92 of 94 individual events in the United States, 1950-2014. Data greater than $7 billion are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is $7.5 million.

Figure 3.2 is a size-cumulative frequency plot for fatalities in the United States for individual hurricanes during the time window 1950-2014. Data greater than 60 fatalities and the data below 50 fatalities are well fit by separate power functions over three orders of magnitude in size. The zone of unfitted data between the two power functions is due to a rapid increase in the number of events between 50 and 60 fatality events and no explanation for this behavior is offered.

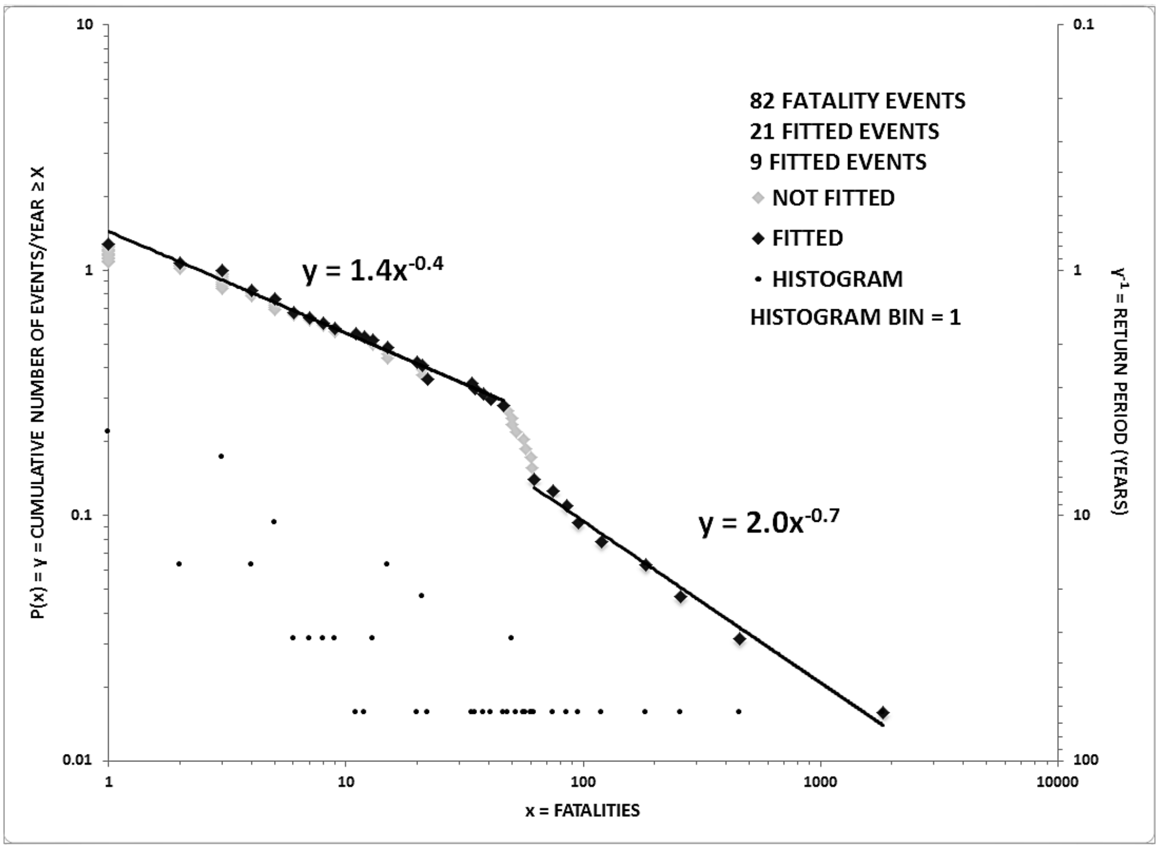


Figure 3.2. Size-cumulative frequency plot of hurricane fatalities for 82 of 94 individual events in the United States, 1950-2014. Data greater than 60 fatalities and the data below 50 fatalities are well fit by separate power functions. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

3.2.2 Earthquakes

Figure 3.3 is a size-cumulative frequency plot for economic losses in the United States for individual earthquakes during the time window 1900-2014. Data greater than $20 million are well fit by a power function over three and a half orders of magnitude in size. The roll-off below $1 million is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

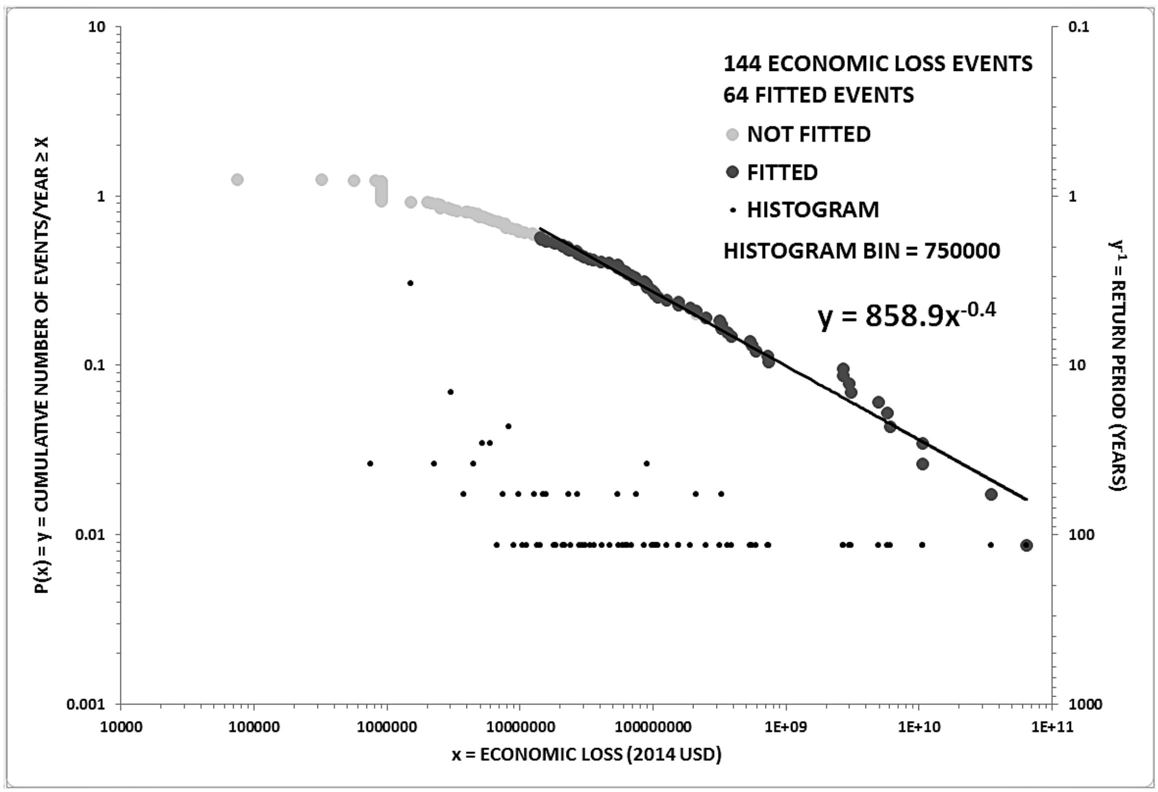


Figure 3.3. Size-cumulative frequency plot of earthquake economic losses for 144 of 196 individual events in the United States, 1900-2014. Data greater than $20 million are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is $750,000.

Figure 3.4 is a size-cumulative frequency plot for fatalities in the United States for individual earthquakes during the time window 1900-2014. Data greater than 5 fatalities are well fit by a power function over two and a quarter orders of magnitude in size. The roll-off below 5 fatalities is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

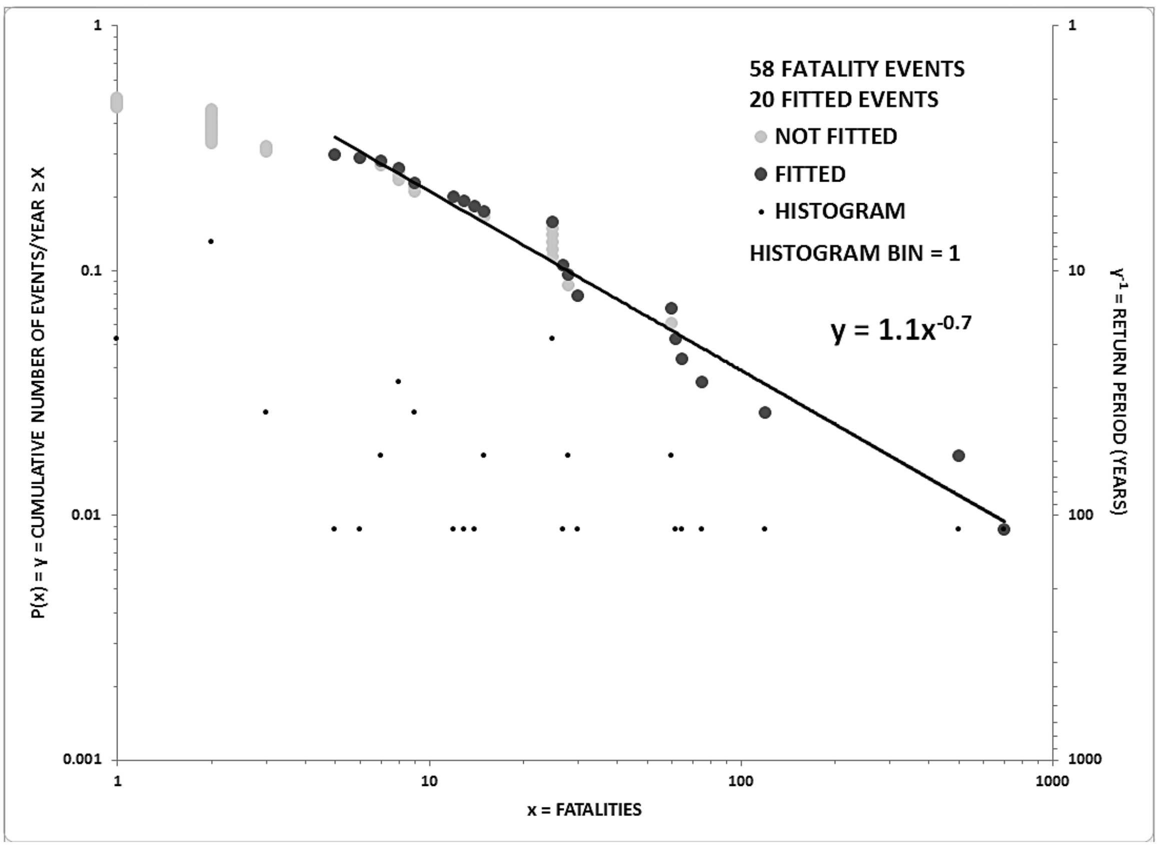


Figure 3.4. Size-cumulative frequency plot of earthquake fatalities for 58 of 196 individual events in the United States, 1900-2014. Data greater than 5 fatalities are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

3.2.3 Tornadoes

Figure 3.5 is a size-cumulative frequency plot for economic losses in the United States for individual tornadoes during the time window 1950-2014. Data between $4 million and $2 billion are well fit by a power function over two and three quarter orders of magnitude in size. The roll-off above $2 billion is indicative of an upper size limit to the power function (Burroughs and Tebbens, 2001). The roll-off below $10,000 is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

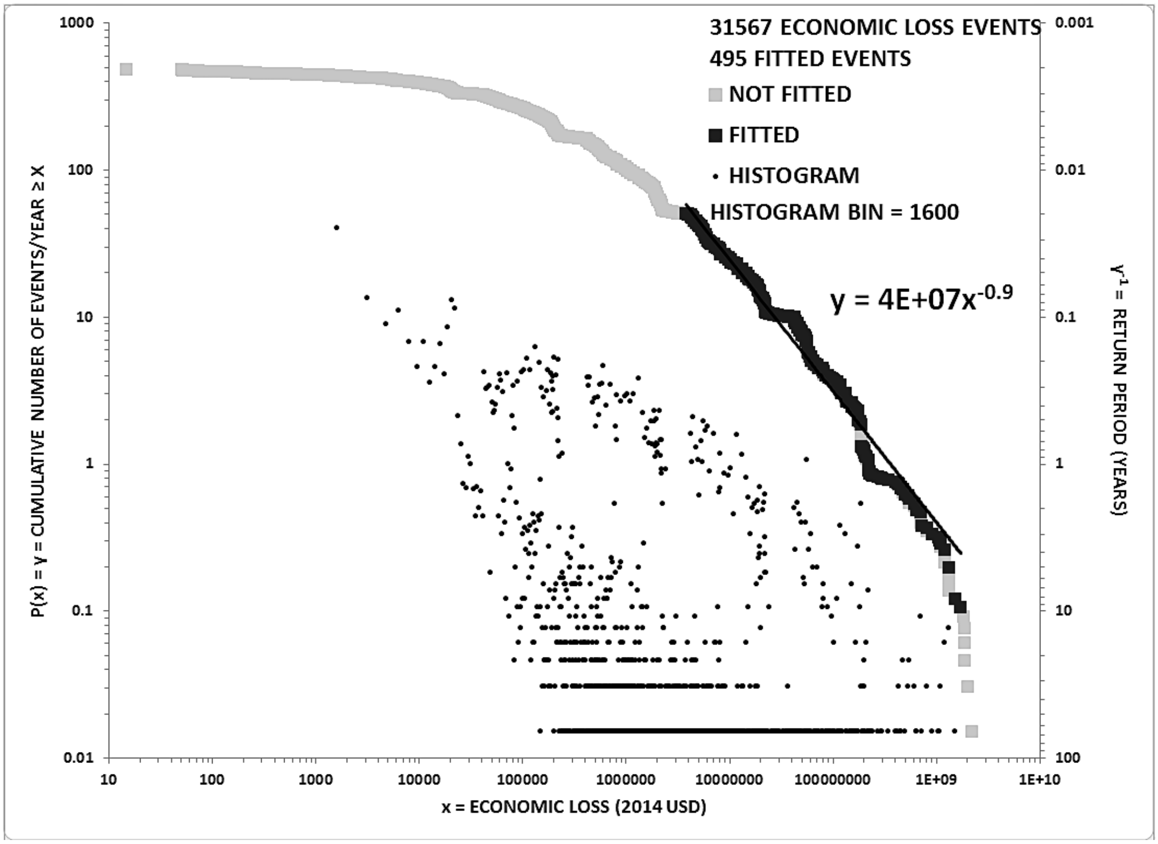


Figure 3.5. Size-cumulative frequency plot of tornado economic losses for 31,567 of 46,402 individual events in the United States, 1900-2014. Data between \$4 million and \$2 billion are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is \$1,600.

Figure 3.6 is a size-cumulative frequency plot for fatalities in the United States for individual tornadoes during the time window 1950-2014. The data greater than 2 fatalities are well fit by a power function over two orders of magnitude in size. The data below 2 fatalities fall away from the power function and is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

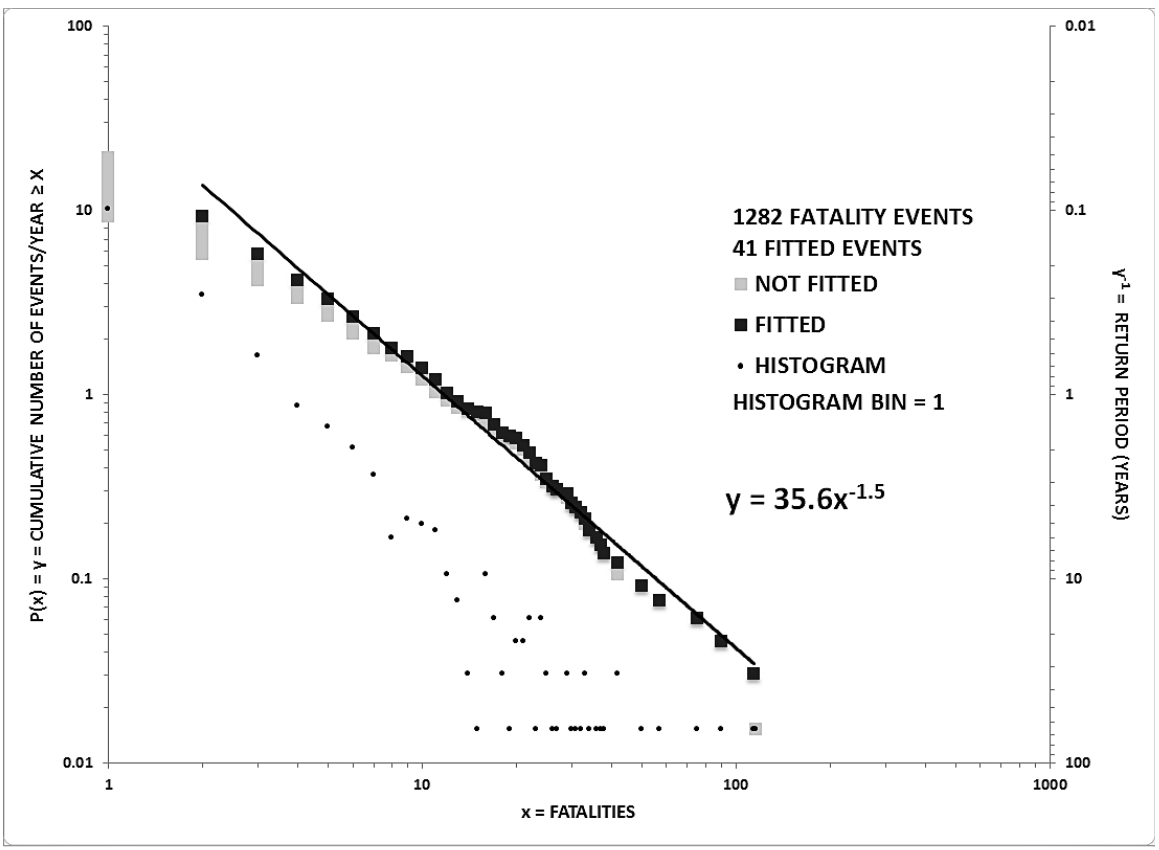


Figure 3.6. Size-cumulative frequency plot of tornado fatalities for 1,282 of 46,402 individual events in the United States, 1900-2014. The data greater than 2 fatalities are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

3.2.4 Floods

Figure 3.7 is a size-cumulative frequency plot for the economic losses in the United States for individual floods during the time window 1996-2014. The data greater than $2 million are well fit by a power function over five orders of magnitude in size. The roll-off below $10,000 is attributed to an under estimate of smaller sized events or a decrease in the number of events with decreasing event size, or to a transition from a power function to a size below which the cumulative number is independent of size, i.e. the data could be fit by a power function with a scaling exponent of zero (a horizontal line).

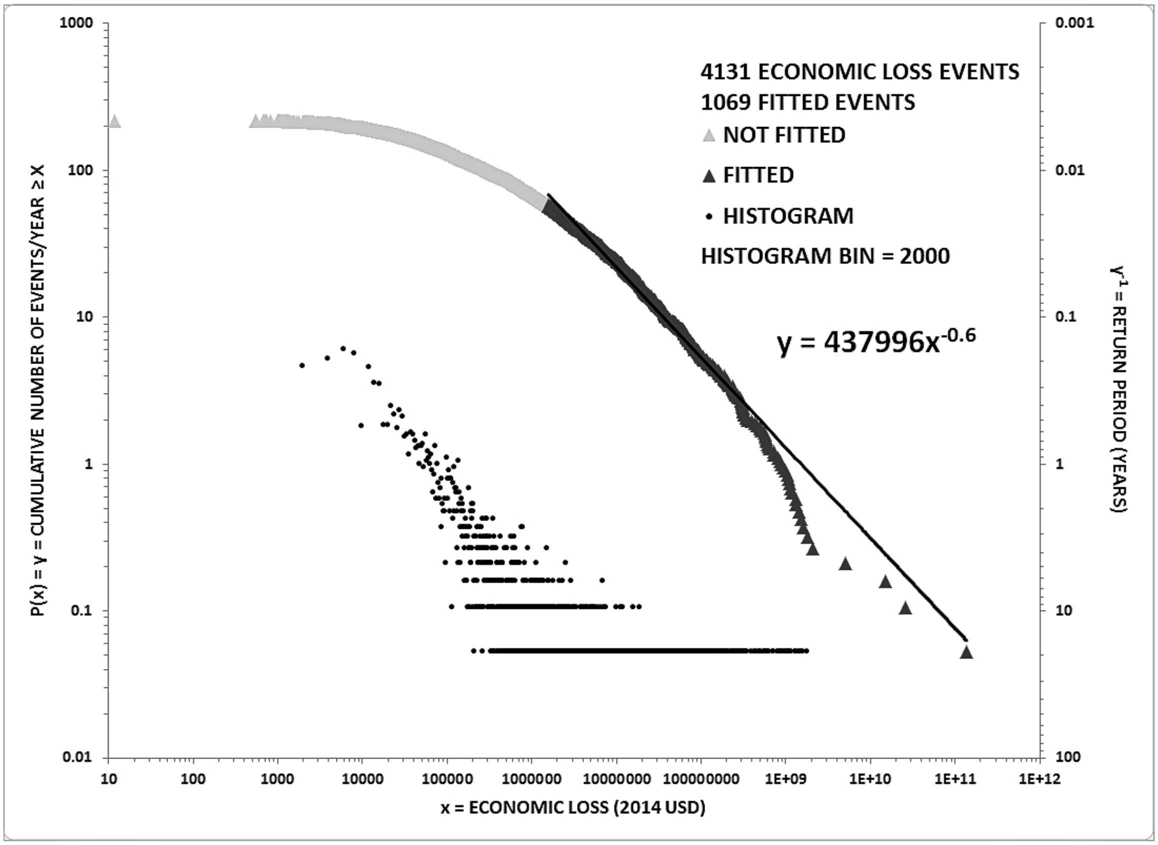


Figure 3.7. Size-cumulative frequency plot of flood economic losses for 4,131 of 6,230 individual events in the United States, 1996-2014. The data greater than \$2 million are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is \$2,000.

Figure 3.8 is a size-cumulative frequency plot for fatalities in the United States for individual floods during the time window 1996-2014. The data greater than 1 fatality are well fit by a power function over one and a half orders of magnitude in size.

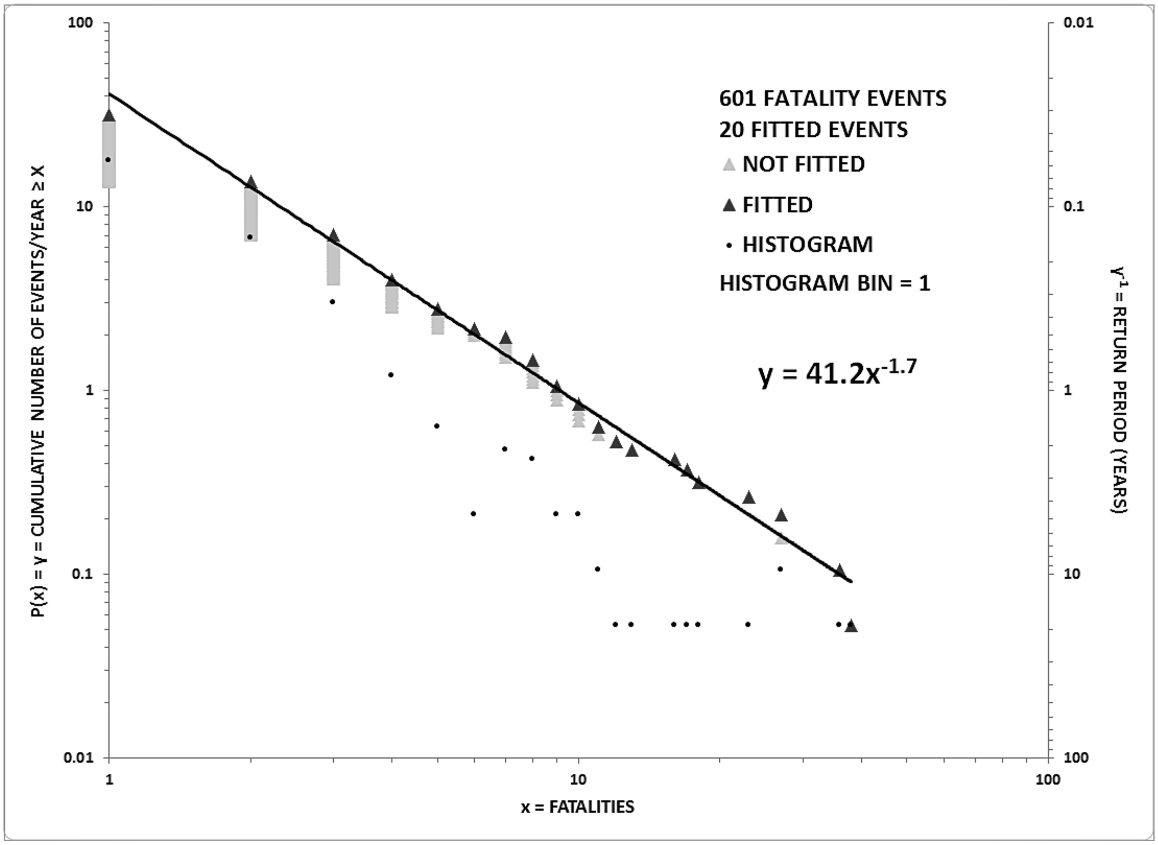


Figure 3.8. Size-cumulative frequency plot of flood fatalities for 601 of 6,230 individual events in the United States, 1996-2014. The data greater than 1 fatality are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1.

3.3 Analysis of Drift in Data Over Time

Improved technology and improved methods of data collection may contribute to drift in the data over time, especially when the time ranges are as long as 1900-2014 (earthquakes), 1950-2014 (hurricanes and tornadoes), and 1996-2014 (floods). It is also possible that climate change may affect the size and number of economic losses and fatalities for weather induced disasters. In order to test for these possible affects, and to test the stability through time of the data, each data set is divided in half by time and each half analyzed with the method used for the entire data set in Section 3.2. Note that when the data was divided in half by time, P(x) was calculated using half of the time interval spanned by the entire data set (ex. 64 year time span for entire data set becomes 32 years for each half of the data set when calculating P(x)). The position of data sets and the position of power functions fit to the data plotted on a size-cumulative frequency plot, is set by the size of the largest data point in the data set. The resulting plots are shown in Appendix E (Figures E.1-E.8 (pages 114-121)) and are summarized in Table 3.1 (page 40).

The scaling exponents for economic loss are within 0.1 of each other for each disaster type indicating that the exponents are stable and unaffected by data collection methodology or by factors such as climate change when the data is separated into halves based on time. The scaling exponents for fatalities depend on disaster size for hurricanes, earthquakes, and tornadoes when the data is separated into halves based on time with larger events having a larger scaling exponent. The scaling exponents for flood fatalities are within 0.1 and 0.2 of each other for each disaster type indicating that the exponents are stable and unaffected by factors such as climate change when the data is separated into halves based on time.

3.4 Composite Size-Cumulative Frequency Plots

Figures 3.9 and 3.10 are composite size-cumulative frequency plots of the economic loss and fatalities for each of the four natural disaster types. The x-axis is economic loss or fatalities for each event. The left y-axis is cumulative number of events per year equal to and greater than X. The right y-axis is return period (in years) of an event of any given size and greater, and is the inverse of the value on the left y-axis. The scaling exponents for economic loss fall into two groups (see Table 3.1 (page 40)). Hurricanes and tornadoes have scaling exponents, $\beta = 1.1$ and 0.9, respectively. Earthquakes and floods have scaling exponents, $\beta = 0.4$ and 0.6, respectively. The scaling exponents for fatalities also fall into two groups. Tornadoes and floods have scaling exponents, $\beta = 1.5$ and 1.7, respectively. Earthquakes and hurricanes have scaling exponents, $\beta = 0.4$ and 0.7, respectively.

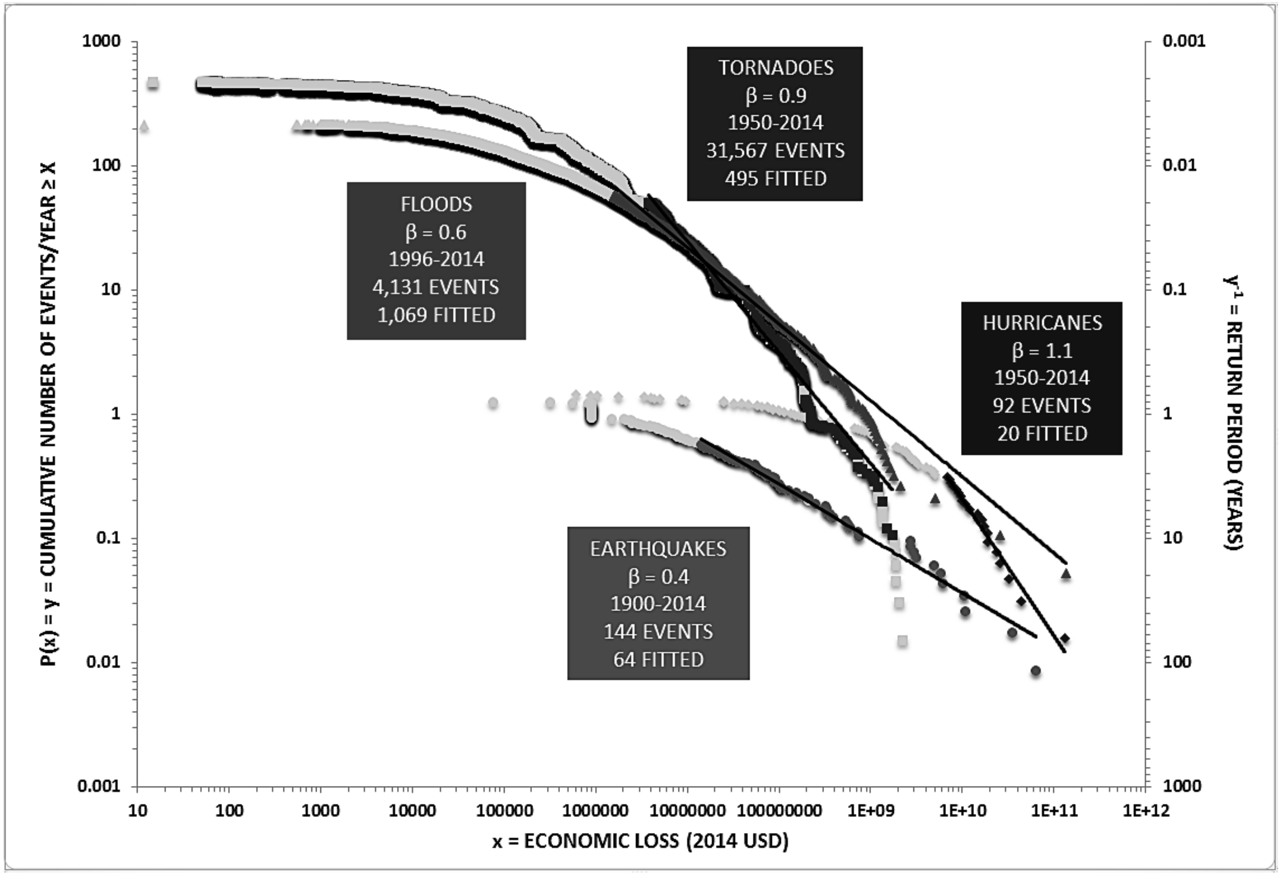


Figure 3.9. Size-cumulative frequency plot of economic losses for individual events for hurricanes, earthquakes, tornadoes, and floods in the United States. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than X. The right y-axis is return period, in years, of an event equal to and greater than X.

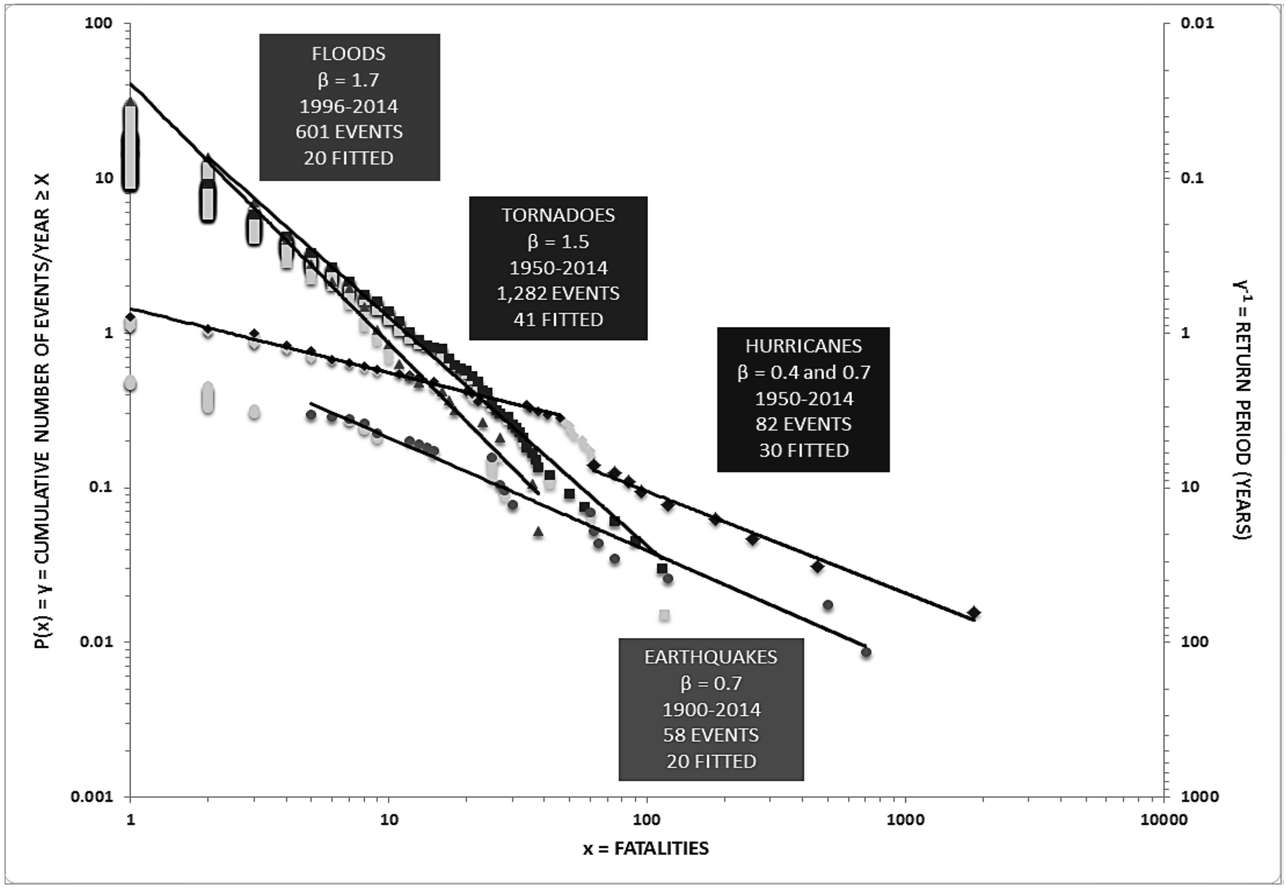


Figure 3.10. Size-cumulative frequency plot of fatalities for individual events for hurricanes, earthquakes, tornadoes, and floods in the United States. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than X. The right y-axis is return period, in years, of an event equal to and greater than X.

Table 3.1. Scaling exponents, β, of power functions fit to economic loss and fatality data for United States hurricanes, earthquakes, tornadoes, and floods. Separate halves of the data based on time are each well fit by a power function (See Figures E.1-E.8 in Appendix E).

DISASTER TYPE	**ECONOMIC LOSS SCALING EXPONENT β**			**FATALITIES SCALING EXPONENT β**		
	1ST HALF DATA SET	**2ND HALF DATA SET**	**ENTIRE DATA SET**	**1ST HALF DATA SET**	**2ND HALF DATA SET**	**ENTIRE DATA SET**
HURRICANE	1.0	1.0	1.1	0.4 and 0.9	0.6 and 2.8	0.4 and 0.7
EARTHQUAKE	0.3	0.4	0.4	0.5	0.4 and 1.6	0.7
TORNADO	1.0	1.0	0.9	1.4	1.2 and 1.9	1.5
FLOOD	0.7	0.6	0.6	1.7	1.5	1.7

Table 3.2. Data and results present study and results. Event type, data source, date range, total number of events, number of economic loss events, number of fatality events, range of economic losses (2014 USD), range of fatalities, number of economic loss events fit by power function, number of fatality events fit by power function, economic loss scaling exponent, β, and fatalities scaling exponent, β.

EVENT TYPE	DATA SOURCE	DATE RANGE	TOTAL # OF INDIVIDUAL EVENTS	# OF ECONOMIC LOSS EVENTS	# OF FATALITY EVENTS	RANGE OF ECONOMIC LOSSES (2014 USD) (Orders of Magnitude in Size)	RANGE OF FATALITIES (Orders of Magnitude in Size)	# OF ECONOMIC LOSS EVENTS FITTED	# OF FATALITY EVENTS FITTED	ECONOMIC LOSS β VALUE	FATALITIES β VALUE
HURRICANE	NOAA NATIONAL HURRICANE CENTER TROPICAL CYCLONE REPORTS	1950-2014	94	92	82	$610,500-$130,680,000,000 (~5.5 Orders)	1-1,833 (~3.2 Orders)	20	30	1.1	0.4 and 0.7
EARTHQUAKE	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1900-2014	196	144	58	$75,200-$64,000,000,000 (~6.0 Orders)	1-700 (~2.75 Orders)	64	20	0.4	0.7
TORNADO	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1950-2014	46,402	31,567	1,282	$14.70-$2,217,500,000 (~8.0 Orders)	1-116 (~2.0 Orders)	495	41	0.9	1.5
FLOOD	NOAA NATIONAL CENTER FOR ENVIRONMENTAL INFORMATION	1996-2014	6,230	4,131	601	$11.70-$134,925,353,120 (~10.0 Orders)	1-38 (~1.5 Orders)	1,069	20	0.6	1.7

CHAPTER 4

DISCUSSION OF RESULTS

4.1 Discussion

The size-cumulative frequency plots presented in Figures 3.1-3.8 (pages 26-35) show data fit with power functions extending from one to five orders of magnitude in size. Size-cumulative frequency composite plots of the economic losses and fatalities data, and power functions fit, are plotted in Figures 3.9-3.10 (pages 38-39) to permit comparison between disaster types, by visual inspection, of the extent of power function behavior, the values of the scaling exponent, the activity level, the probability of occurrence of any given event size in any given year, and the return period.

A roll-off of the data for larger losses was not addressed by Nishenko and Barton, 1996, but is now interpreted to indicate an upper limit to the size of the largest event following Burroughs and Tebbens, 2001. Roll-off of the data to a slope of zero for the smallest sizes was not addressed by Barton and Nishenko, 1996 either, but is now interpreted to indicate that below a certain size, the number of losses is constant i.e. independent of size.

4.2 Comparison of Results to Previous Studies

Table 1.1 (page 6) summarizes the results of Barton and Nishenko (1994) and Nishenko and Barton (1996). Table 3.2 (page 41) summarizes the results of the present study. The time spanned in the present study for both economic loss and fatalities is shorter for three of the disaster types (hurricanes: 1950-2014, tornadoes: 1950-2014, and floods 1996-2014) than in the previous studies (1900-1989). The time spanned in the present study, for earthquakes (1900-2014), is longer than in the previous studies (1900-1989). The total number of all the events, from smallest to largest, in the present study is larger (94-46,402) than in the previous studies (44-56). The size range of all economic losses is larger in the present study ($11.70-$134,925,353,120) (2014 USD) than in the previous studies ($1 million-$6 billion) (1990 USD). The size range of all fatalities in the present study (1-1,833) is smaller than in the previous studies (1-5,900), perhaps due in part to improvements in advanced warning systems for weather related disasters. The scaling exponents for all disaster types are equal to and greater in the present study (0.4-1.7) than in previous studies (0.4-1.4). Even though the scaling exponents have not changed much over the past twenty years from the previous studies to this present study, the size of total number of events and the range over which the events scale is much larger.

Where there is more than one event of a given size plotted on a size-cumulative frequency plot, then only the topmost repetitive event size should be used when fitting a power function to the data (Burroughs and Tebbens, 2001). Barton and Nishenko (1994) fit power functions to all of the data including repetitive event sizes which slightly depressed the values they found for scaling exponents (Figures 1.1 (page 4) and 1.2 (page 5) and Table 1.1 (page 6)).

4.2.1 Economic Loss

The time spanned for economic loss events in the present study for hurricanes is shorter (1950-2014) than in previous studies (1900-1989). The time spanned for economic loss events in the present study for earthquakes is longer (1900-2014) than in previous studies (1900-1989). The number of economic loss events in the present study for hurricanes and earthquakes is larger (92-144) than in previous studies (27-49). The size range of economic loss values in this study for hurricanes and earthquakes is larger ($75,200-$130,680,000,000) (2014 USD) than previous studies ($1 million-$6 billion) (1990 USD). The scaling exponent for hurricanes in the present study, $\beta = 1.1$, is greater than in previous studies, $\beta = 0.6$. The scaling exponent for earthquakes in the present study, $\beta = 0.4$, is the same as in previous studies, $\beta = 0.4$.

4.2.2 Fatalities

The time spanned for fatality events in the present study for three disaster types is shorter (hurricanes: 1950-2014, tornadoes 1950-2014, and floods: 1996-2014) than in previous studies (1900-1989). The time spanned for fatality events in the present study for earthquakes is longer (1900-2014) than in previous studies (1900-1989). The size range of fatality values in this study (1-1,833) is smaller than previous studies (1-5,900). Even though there have been more events (58-1,282) than the previous study (28-56), the quality of improved warning systems (http://earthquake.usgs.gov/research/earlywarning/ and http://www.nhc.noaa.gov/prepare/wwa.php) may have contributed to smaller fatalities for weather related disasters. The scaling exponent for hurricanes is, $\beta = 0.4$ and 0.7, which is less than and greater than in previous studies, $\beta = 0.6$. The scaling exponent for earthquakes is, $\beta = 0.7$, greater than in previous studies, $\beta = 0.4$. The scaling exponent for tornadoes is, $\beta = 1.5$, greater than in previous studies, $\beta = 1.4$. The scaling exponent for floods is, $\beta = 1.7$, greater than in previous studies, $\beta = 1.3$. The grouping of floods and tornadoes, and hurricanes and earthquakes, based on similar scaling exponents, found in the present study was also found by Barton and Nishenko (1994).

4.3 Probabilistic Forecasting and the Return Period for Individual Natural Disaster Events as a Function of Size of Loss

To calculate forecasts for the probability of occurrence of an event, for any of the four natural disasters, the present study will use a Poisson distribution:

$$P(n \geq 1, t, \tau) = 1 - e^{-t/\tau}$$

where:

n = the number of events

t = the probability of occurrence (number of years)

τ = the return period of an event

This equation is given as equation 1.2 in Feller (1971), where expectation = $\tau = \alpha$. There are associated assumptions that must be taken into account when using a Poisson distribution (Feller, pp.12). The occurrence of one event does not affect the probability that a second event will occur, meaning the events are independent of previous events. The rate at which events occur over time is constant. Two events of the same natural disaster cannot occur at exactly the same instant.

To calculate the return period needed for computation of the Poisson distribution, refer to the power function equations from Figures 3.1-3.8 (pages 26-35). Replacing x with the value of the economic loss or fatalities, and taking the inverse of the result gives the return period. The present study evaluates the probability of occurrence for economic losses resulting from events with $10 million and $10 billion and greater, and fatalities resulting from events with 10 and 100 and greater. Replacing t and τ with their respective values from the equation above, a probability of occurrence value can be obtained for each natural disaster over an infinite time window.

Determination of the return period for an event of a given size and greater provides a basis for establishing insurance rates, building codes, and disaster relief agencies' response plans for natural disasters over a range of magnitudes in size. The return period is an estimate of the likelihood of an event based on historical data collected, not its periodic recurrence. Return period is not interpreted to mean an event will occur within that time window, but it offers the idea that an event of a specific magnitude in size and greater could occur (i.e. A 100-year flood is not interpreted to occur regularly every 100 years. It might occur once, twice, or not at all in a 100- year time window). The probabilities provided in Tables 4.1 (page 48) and 4.2 (page 49) represent a per year percentage, within the total number of years, that an event could occur. Economic loss data is provided in Table 4.1 for each of the four natural disaster types with probability of occurrence for events of $10 million and $10billion and greater, as well as their estimated return period in years. For example, in the United States, a hurricane with an economic loss value of $10 billion and greater has the probability to occur 0.86 times per year over a 10 year time window. So the return period for a hurricane event with $10 billion economic losses and greater is 5 years. The probability of the occurrence of a tornado event in any given year with economic losses of $10 million and greater is 99%, with a return period of 0.05 years. Fatality data is provided in Table 4.2 for each of the four natural disaster types with probability of occurrence for events of 10 and 100 fatalities and greater, as well as their estimated return period in years.

Table 4.1 Probability estimates for the occurrence of hurricane, earthquake, tornado, and flood events with $10,000,000 and $10,000,000,000 and greater economic losses per event in the United States during 1, 10, and 50 year exposure times, and estimates of the mean return period in years. Empty box values not used due to roll-off from power function.

EXPOSURE TIME / DISASTER	PROBABILITY OF OCCURRENCE 1 YEAR		PROBABILITY OF OCCURRENCE 10 YEARS		PROBABILITY OF OCCURRENCE 50 YEARS		RETURN PERIOD (YEARS)	
	$10,000,000 AND GREATER PER EVENT	**$10,000,000,000 AND GREATER PER EVENT**	**$10,000,000 AND GREATER PER EVENT**	**$10,000,000,000 AND GREATER PER EVENT**	**$10,000,000 AND GREATER PER EVENT**	**$10,000,000,000 AND GREATER PER EVENT**	**$10,000,000 AND GREATER PER EVENT**	**$10,000,000,000 AND GREATER PER EVENT**
HURRICANE	-----	0.18*	-----	0.86	-----	>0.99	-----	5
EARTHQUAKE	0.75	0.08	>0.99	0.58	>0.99	0.99	0.73	11.64
TORNADO	>0.99	0.04 (extrapolation)	>0.99	0.33 (extrapolation)	>0.99	0.86 (extrapolation)	0.05	25 (extrapolation)
FLOOD	0.94	0.36	>0.99	0.99	>0.99	>0.99	0.36	2.28

Table 4.2 Probability estimates for the occurrence of hurricane, earthquake, tornado, and flood events with 10 and 100 fatalities and greater per event in the United States during 1, 10, and 50 year exposure times, and estimates of the mean return period in years.`

EXPOSURE TIME / DISASTER	PROBABILITY OF OCCURRENCE 1 YEAR		PROBABILITY OF OCCURRENCE 10 YEARS		PROBABILITY OF OCCURRENCE 50 YEARS		RETURN PERIOD (YEARS)	
	10 FATALITIES AND GREATER PER EVENT	100 FATALITIES AND GREATER PER EVENT	10 FATALITIES AND GREATER PER EVENT	100 FATALITIES AND GREATER PER EVENT	10 FATALITIES AND GREATER PER EVENT	100 FATALITIES AND GREATER PER EVENT	10 FATALITIES AND GREATER PER EVENT	100 FATALITIES AND GREATER PER EVENT
HURRICANE	0.43*	0.08	>0.99	0.55	>0.99	0.98	1.79	12.56
EARTHQUAKE	0.20	0.04	0.89	0.35	>0.99	0.89	4.56	22.84
TORNADO	0.67	0.03	>0.99	0.30	>0.99	0.83	0.89	28.09
FLOOD	0.56	0.02 (extrapolation)	>0.99	0.15 (extrapolation)	>0.99	0.56 (extrapolation)	1.22	60.97 (extrapolation)

* 0.43 = 43% Probability of Occurrence

CHAPTER 5

CONCLUSIONS

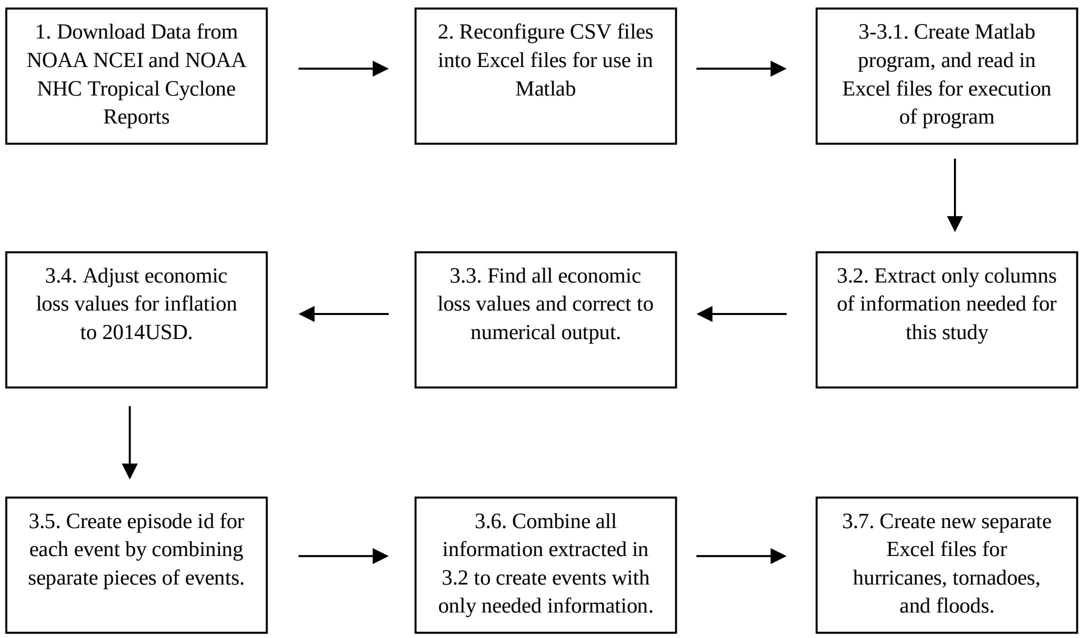
Size-cumulative frequency plots of economic losses and fatalities for individual events due to hurricanes, earthquakes, tornadoes, and floods are well fit by power functions, over one to five orders of magnitude in size, with exponents between 0.4 and 1.7. The scaling exponents for economic loss fall into two groups (see Table 3.1 (page 40)). Tornadoes and hurricanes have scaling exponents, β = 0.9 and 1.1, respectively, while earthquakes and floods have scaling exponents, β = 0.4 and 0.6, respectively. The scaling exponents for fatalities also fall into two groups. Floods and tornadoes have scaling exponents, β = 1.5 and 1.7, respectively, while hurricanes and earthquakes have scaling exponents, β = 0.4 and 0.7, respectively.

Determination of the return period for an event of a given size and greater provides a basis for establishing insurance rates, building codes, and disaster relief agency response plans for natural disasters over a range of magnitudes in size. The return period, based on historical data, is not interpreted to mean an event will occur within that time window, but it offers the idea that an event of a specific magnitude in size and greater could occur (i.e. A 100-year flood is not interpreted to occur regularly every 100 years. It might occur once, twice, or not at all in a 100-year time window). The probabilities provided in Tables 4.1 and 4.2 represent a per year percentage, within the total number of years, that an event could occur. Economic loss data is provided in

Table 4.1 for each of the four natural disaster types with probability of occurrence for events of \$10 million and \$10 billion and greater, as well as the estimated return period in years. Fatality data is provided in Table 4.2 for each of the four natural disaster types with probability of occurrence for events of 10 and 100 fatalities and greater, as well as their estimated return period in years. For example, in the United States, an earthquake with a fatality value of 100 and greater has the probability to occur 0.89 times per year over a 100-year time window. So the return period for an earthquake event with 100 fatalities and greater is 22.84 years. The probability of the occurrence of a flood event in any given year with 100 fatalities and greater is 2% (based on extrapolation of power function from Figure 3.8 (page 35)), with a return period of 60.97 years.

APPENDIX A

Step-by-Step Extraction of Data from the NOAA Databases and MATLAB Computer Code for Grouping Data into Events.



Data files for all four natural disaster types from the national databases were extracted in comma separated value files, and reconfigured into Excel files which were imported to a custom Matlab computer program that sorted and grouped the data into individual events. The step-by-step procedure for extracting the data from the national database and reconfiguring it into Excel is given below.

1. Gather data from NOAA National Center for Environmental Information in Comma Separated Value files.
   1.1. Go to ftp://ftp.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/ for tornadoes floods;

      http://www.nhc.noaa.gov/data/#tcr for hurricanes; and

      http://www.ngdc.noaa.gov/nndc/struts/form?t=101650&s=1&d=1 for earthquakes.
2. Download files for the range of years available to retrieve all weather related incidents recorded for separate weather disasters. During the years 1950-1954, only tornadoes were kept on record. During the years 1955-1992, tornado, thunderstorms, wind, and hail were recorded. From 1996-present, 48 different event types are recorded. Open each comma separated value file and then save as an Excel file for use by the Matlab computer program.

3. The following Matlab program reads in the reconfigured Excel files from national databases, sorts and groups the data based on specified criteria (episode id to create individual events), and outputs new Excel files that contain the sorted and grouped data (ex. Table C.2 (page 95)). Economic loss data was transformed from the national database form into a monetary value form (ex. 1M = 1000000) and then multiplied by an inflation amount, based on year, to get the monetary values to 2014USD by the Matlab program. The program groups the data into individual events and sums the values within each event. Fatality data is also grouped into individual events and summed. The final step is to create an Excel file for each disaster types (hurricanes,

tornadoes, floods (including: floods, flash floods, marine floods, and coastal floods).

Note: Earthquake and hurricane final data comes from a different data source.

```
fn=dir;
MONTH_NAME=[]; %column L
YEAR=[]; %column K
BEGIN_YEARMONTH=[]; %column A
BEGIN_DAY=[]; %column B
END_YEARMONTH=[]; %column D
END_DAY=[]; %column E
EPISODEID=[]; %column G
STATE=[]; %column I
EVENT_TYPE=[]; %column M
DIRECTINJURIES=[]; %column U
INDIRECTINJURIES=[]; %column V
DIRECTFATALITIES=[]; %column W
INDIRECTFATALITIES=[]; %column X
PROPDAMAGE=[]; %column Y
CROPDAMAGE=[]; %column Z
NARRATIVE=[]; %column AW
NARRATIVE2=[]; %column AX
```

3.1
```
for i=(7:length(fn))
    if ~fn(i).isdir
        fn(i).name
        [pathstr,name,ext] = fileparts(fn(i).name);
        if strcmp(ext,'.xlsx')==1
            [num,txt,raw]=xlsread(fn(i).name);
```

3.2

```
MONTH_NAME=[MONTH_NAME;txt(2:end,12)];
%gives the month the event started

YEAR=[YEAR;num(1:end,11)];
%gives the year the event started/happened

BEGIN_YEARMONTH=[BEGIN_YEARMONTH;num(1:end,1)];
%gives the month and year of event start

BEGIN_DAY=[BEGIN_DAY;num(1:end,2)];
%gives the day the event started

END_YEARMONTH=[END_YEARMONTH;num(1:end,4)];
%gives the month and year the event ended

END_DAY=[END_DAY;num(1:end,5)];
%gives the day the event ended

EPISODEID=[EPISODEID;num(1:end,7)];
%gives each individual episode

STATE=[STATE;txt(2:end,9)];
%gives the state the event happened in

EVENT_TYPE=[EVENT_TYPE;txt(2:end,13)];
%gives specific event we need before assigning damage value
```

```
        DIRECTINJURIES=[DIRECTINJURIES;num(1:end,21)];
        %gives number of injuries directly from each event

        INDIRECTINJURIES=[INDIRECTINJURIES;num(1:end,22)];
        %gives number of injuries due to outside circumstances for each
        %event

        DIRECTFATALITIES=[DIRECTFATALITIES;num(1:end,23)];
        %gives the fatalities from each event

        INDIRECTFATALITIES=[INDIRECTFATALITIES;num(1:end,24)];
        %gives the number of fatalities caused by the event but
        %happened after event was over.

        PROPDAMAGE=[PROPDAMAGE;txt(2:end,25)];
        %gives property damage from each event

        CROPDAMAGE=[CROPDAMAGE;txt(2:end,26)];
        %gives crop damage from each event

        NARRATIVE=[NARRATIVE;txt(2:end,49)];

        NARRATIVE2=[NARRATIVE2;txt(2:end,50)];

    end
end
```

```
end

%find all different values needed to produce wanted output.
```

3.3

```
FindhProp=strfind(PROPDAMAGE,'h');
FindHProp=strfind(PROPDAMAGE,'H');
FindkProp=strfind(PROPDAMAGE,'k');
FindKProp=strfind(PROPDAMAGE,'K');
FindMProp=strfind(PROPDAMAGE,'M');
FindBProp=strfind(PROPDAMAGE,'B');
FindTProp=strfind(PROPDAMAGE,'T');

FindhCrop=strfind(CROPDAMAGE,'h');
FindHCrop=strfind(CROPDAMAGE,'H');
FindkCrop=strfind(CROPDAMAGE,'k');
FindKCrop=strfind(CROPDAMAGE,'K');
FindMCrop=strfind(CROPDAMAGE,'M');
FindBCrop=strfind(CROPDAMAGE,'B');
FindTCrop=strfind(CROPDAMAGE,'T');

%separates each of the values into the different categories that we need.

LenD=length(PROPDAMAGE);
DPROP=zeros(LenD,1);
DCROP=zeros(LenD,1);

%DPROP array of all 0 values
```

```
%DCROP array of all 0 values

%take the array and find specific values to change them into the numbers
%we need to use so we can find plot them.  Using a for loop, we use i
%from 1 to the length and if/else statements. If K(i) is not empty (K is
%in the string), then replace the K with a blank and multiple by
%1000...carry on though h, H, M, and B, if nothing then transfer value as is.

for l=(1:LenD)
    if ~isempty(FindhProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'h',''))*100;
        %replace all strings of h with the value*100
    elseif ~isempty(FindHProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'H',''))*100;
        %replace all strings of H with the value*100
    elseif ~isempty(FindkProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'k',''))*1000;
        %replace all strings of k with the value*1000
    elseif ~isempty(FindKProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'K',''))*1000;
        %replace all strings of K with the value*1000
    elseif ~isempty(FindMProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'M',''))*1000000;
        %replace all strings of M with the value*1000000
    elseif ~isempty(FindBProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'B',''))*1000000000;
        %replace all strings of B with the value*1000000000
```

```
    elseif ~isempty(FindTProp{l})
        DPROP(l)=str2num(strrep(PROPDAMAGE{l},'T',''))*1000000000000;
        %replace all strings of T with the value*1000000000000
    elseif length(PROPDAMAGE{l})==0
        DPROP(l)==0;
        %if the cell is empty(blank), then replace with 0
    else
        DPROP(l)=str2num(PROPDAMAGE{l});
        %carryover all other values
    end
end

for j=(1:LenD)
    if ~isempty(FindhCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'h',''))*100;
        %replace all strings of h with the value*100
    elseif ~isempty(FindHCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'H',''))*100;
        %replace all strings of H with the value*100
    elseif ~isempty(FindkCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'k',''))*1000;
        %replace all strings of k with the value*1000
    elseif ~isempty(FindKCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'K',''))*1000;
        %replace all strings of K with the value*1000
    elseif ~isempty(FindMCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'M',''))*1000000;
```

```
        %replace all strings of M with the value*1000000
    elseif ~isempty(FindBCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'B',''))*1000000000;
        %replace all strings of B with the value*1000000000
    elseif ~isempty(FindTCrop{j})
        DCROP(j)=str2num(strrep(CROPDAMAGE{j},'T',''))*1000000000000;
        %replace all strings of T with the value*1000000000000
    elseif length(CROPDAMAGE{j})==0
        DCROP(j)==0;
        %if the cell is empty(blank), then replace with 0
    else
        DCROP(j)=str2num(CROPDAMAGE{j});
        %carryover all other values
    end
end


%Get the total damage amount by adding the two amounts(DPROP+DCROP), make
%sure you have the same amount of rows in the columns, otherwise it will
%return an error


DAMAGETHEN=[DCROP+DPROP];
ADJUSTEDDAMAGENOW=DAMAGETHEN;


INJURIES=DIRECTINJURIES+INDIRECTINJURIES;
FATALITIES=DIRECTFATALITIES+INDIRECTFATALITIES;
```

3.4

```
for YR=(1950:2014);
```

```
idx=find(YEAR==YR);
if YR==1950;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*9.82;
elseif YR==1951;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*9.11;
elseif YR==1952;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.93;
elseif YR==1953;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.87;
elseif YR==1954;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.80;
elseif YR==1955;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.83;
elseif YR==1956;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.70;
elseif YR==1957;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.42;
elseif YR==1958;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.19;
elseif YR==1959;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.14;
elseif YR==1960;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*8.00;
elseif YR==1961;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.92;
elseif YR==1962;
   ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.84;
```

```
elseif YR==1963;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.74;
elseif YR==1964;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.64;
elseif YR==1965;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.52;
elseif YR==1966;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.31;
elseif YR==1967;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*7.09;
elseif YR==1968;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*6.80;
elseif YR==1969;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*6.45;
elseif YR==1970;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*6.10;
elseif YR==1971;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*5.85;
elseif YR==1972;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*5.66;
elseif YR==1973;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*5.33;
elseif YR==1974;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*4.80;
elseif YR==1975;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*4.40;
elseif YR==1976;
```

```
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*4.16;
elseif YR==1977;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*3.91;
elseif YR==1978;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*3.63;
elseif YR==1979;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*3.26;
elseif YR==1980;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.87;
elseif YR==1981;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.60;
elseif YR==1982;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.45;
elseif YR==1983;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.38;
elseif YR==1984;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.28;
elseif YR==1985;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.20;
elseif YR==1986;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.16;
elseif YR==1987;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.08;
elseif YR==1988;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*2.00;
elseif YR==1989;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.91;
```

```
elseif YR==1990;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.81;
elseif YR==1991;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.74;
elseif YR==1992;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.69;
elseif YR==1993;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.64;
elseif YR==1994;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.60;
elseif YR==1995;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.55;
elseif YR==1996;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.51;
elseif YR==1997;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.47;
elseif YR==1998;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.45;
elseif YR==1999;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.42;
elseif YR==2000;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.37;
elseif YR==2001;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.34;
elseif YR==2002;
    ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.32;
elseif YR==2003;
```

```
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.29;
    elseif YR==2004;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.25;
    elseif YR==2005;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.21;
    elseif YR==2006;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.17;
    elseif YR==2007;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.14;
    elseif YR==2008;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.10;
    elseif YR==2009;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.10;
    elseif YR==2010;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.09;
    elseif YR==2011;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.05;
    elseif YR==2012;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.03;
    elseif YR==2013;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.02;
    elseif YR==2014;
        ADJUSTEDDAMAGENOW(idx)=ADJUSTEDDAMAGENOW(idx)*1.00;
    end
end
```

3.5

```
UEPISODEID=unique(EPISODEID);
```

```
for k=1:length(UEPISODEID)
    begin1=[1]
    k
    idx=find(EPISODEID==UEPISODEID(k));
    %if ~fn(i).isdir
    %    fn(i).name
        if length(idx)>1;

ADJUSTEDDAMAGENOW(idx(1))=sum(ADJUSTEDDAMAGENOW(idx));
            ADJUSTEDDAMAGENOW(idx(2:end))=[];
            DAMAGETHEN(idx(1))=sum(DAMAGETHEN(idx));
            DAMAGETHEN(idx(2:end))=[];
            %will be used when needing to look at unadjusted vs adjusted for
            %plots and for report to show difference
            INJURIES(idx(1))=sum(INJURIES(idx));
            INJURIES(idx(2:end))=[];
            FATALITIES(idx(1))=sum(FATALITIES(idx));
            FATALITIES(idx(2:end))=[];
            MONTH_NAME(idx(2:end))=[];
            YEAR(idx(2:end))=[];
            BEGIN_YEARMONTH(idx(2:end))=[];
            BEGIN_DAY(idx(2:end))=[];
            END_YEARMONTH(idx(2:end))=[];
            END_DAY(idx(2:end))=[];
            STATE(idx(2:end))=[];
            EVENT_TYPE(idx(2:end))=[];
            EPISODEID(idx(2:end))=[];
            NARRATIVE(idx(2:end))=[];
```

```
            NARRATIVE2(idx(2:end))=[];
        end
    %end
    finish2=[2]
end

%Get individual event types output into individual matrices.
```

3.6 & 3.7

```
FindTornado=strcmpi(EVENT_TYPE,'Tornado');

T1=MONTH_NAME(FindTornado>0);
T2=YEAR(FindTornado>0);
T3=BEGIN_YEARMONTH(FindTornado>0);
T4=BEGIN_DAY(FindTornado>0);
T5=END_YEARMONTH(FindTornado>0);
T6=END_DAY(FindTornado>0);
T7=UEPISODEID(FindTornado>0);
T8=STATE(FindTornado>0);
T8=strrep(T8,' ',");
T9=EVENT_TYPE(FindTornado>0);
T9=strrep(T9,' ',");
T10=INJURIES(FindTornado>0);
T11=FATALITIES(FindTornado>0);
T12=DAMAGETHEN(FindTornado>0);
T13=ADJUSTEDDAMAGENOW(FindTornado>0);
%each of the different variables we want in our output
```

```
TORNADOFILE=cell(length(T1),13);
%filename=cell(length(T#),columns)

TORNADOFILE(:,1)=T1(:);
TORNADOFILE(:,2)=num2cell(T2(:));
TORNADOFILE(:,3)=num2cell(T3(:));
TORNADOFILE(:,4)=num2cell(T4(:));
TORNADOFILE(:,5)=num2cell(T5(:));
TORNADOFILE(:,6)=num2cell(T6(:));
TORNADOFILE(:,7)=num2cell(T7(:));
TORNADOFILE(:,8)=T8(:);
TORNADOFILE(:,9)=T9(:);
TORNADOFILE(:,10)=num2cell(T10(:));
TORNADOFILE(:,11)=num2cell(T11(:));
TORNADOFILE(:,12)=num2cell(T12(:));
TORNADOFILE(:,13)=num2cell(T13(:));
%=T1 means a cell array,=num2cell means a number originally convert to cell

  fileID = fopen('TORNADOFILE.dat','w');
  %gives file name for output but leave .dat
  formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f\n';
  %fprintf in help to see different values

  [nrows,ncols] = size(TORNADOFILE);

  HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s\n';
```

```
HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',...
        'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
        'DamageThen','Adjusted(2014)DamageNow'};
    fprintf(fileID,HformatSpec,HEADER{1,:});

for row = 1:nrows
    fprintf(fileID,formatSpec,TORNADOFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file

FindHurricane=strcmpi(EVENT_TYPE,'Hurricane (Typhoon)');

H1=MONTH_NAME(FindHurricane>0);
H2=YEAR(FindHurricane>0);
H3=BEGIN_YEARMONTH(FindHurricane>0);
H4=BEGIN_DAY(FindHurricane>0);
H5=END_YEARMONTH(FindHurricane>0);
H6=END_DAY(FindHurricane>0);
H7=UEPISODEID(FindHurricane>0);
H8=STATE(FindHurricane>0);
H8=strrep(H8,' ',");
H9=EVENT_TYPE(FindHurricane>0);
H9=strrep(H9,' ',");
H10=INJURIES(FindHurricane>0);
H11=FATALITIES(FindHurricane>0);
```

```
H12=DAMAGETHEN(FindHurricane>0);
H13=ADJUSTEDDAMAGENOW(FindHurricane>0);
%each of the different variables we want in our output

HURRICANEFILE=cell(length(H1),13);
%filename=cell(length(H#),columns)

HURRICANEFILE(:,1)=H1(:);
HURRICANEFILE(:,2)=num2cell(H2(:));
HURRICANEFILE(:,3)=num2cell(H3(:));
HURRICANEFILE(:,4)=num2cell(H4(:));
HURRICANEFILE(:,5)=num2cell(H5(:));
HURRICANEFILE(:,6)=num2cell(H6(:));
HURRICANEFILE(:,7)=num2cell(H7(:));
HURRICANEFILE(:,8)=H8(:);
HURRICANEFILE(:,9)=H9(:);
HURRICANEFILE(:,10)=num2cell(H10(:));
HURRICANEFILE(:,11)=num2cell(H11(:));
HURRICANEFILE(:,12)=num2cell(H12(:));
HURRICANEFILE(:,13)=num2cell(H13(:));
%=H1 means a cell array,=num2cell means a number originally convert to cell

  fileID = fopen('HURRICANEFILE.dat','w');
  %gives file name for output but leave .dat
  formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f\n';
  %fprintf in help to see different values
```

```
    [nrows,ncols] = size(HURRICANEFILE);


    HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s\n';

HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',...
        'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
        'DamageThen','Adjusted(2014)DamageNow'};
    fprintf(fileID,HformatSpec,HEADER{1,:});


for row = 1:nrows
    fprintf(fileID,formatSpec,HURRICANEFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file


FindFlood=strcmpi(EVENT_TYPE,'Flood');


F1=MONTH_NAME(FindFlood>0);
F2=YEAR(FindFlood>0);
F3=BEGIN_YEARMONTH(FindFlood>0);
F4=BEGIN_DAY(FindFlood>0);
F5=END_YEARMONTH(FindFlood>0);
F6=END_DAY(FindFlood>0);
F7=UEPISODEID(FindFlood>0);
F8=STATE(FindFlood>0);
F8=strrep(F8,' ','');
F9=EVENT_TYPE(FindFlood>0);
```

```
F9=strrep(F9,' ','');
F10=INJURIES(FindFlood>0);
F11=FATALITIES(FindFlood>0);
F12=DAMAGETHEN(FindFlood>0);
F13=ADJUSTEDDAMAGENOW(FindFlood>0);
F14=NARRATIVE(FindFlood>0);
F15=NARRATIVE2(FindFlood>0);
%each of the different variables we want in our output


FLOODFILE=cell(length(F1),15);
%filename=cell(length(F#),columns)


FLOODFILE(:,1)=F1(:);
FLOODFILE(:,2)=num2cell(F2(:));
FLOODFILE(:,3)=num2cell(F3(:));
FLOODFILE(:,4)=num2cell(F4(:));
FLOODFILE(:,5)=num2cell(F5(:));
FLOODFILE(:,6)=num2cell(F6(:));
FLOODFILE(:,7)=num2cell(F7(:));
FLOODFILE(:,8)=F8(:);
FLOODFILE(:,9)=F9(:);
FLOODFILE(:,10)=num2cell(F10(:));
FLOODFILE(:,11)=num2cell(F11(:));
FLOODFILE(:,12)=num2cell(F12(:));
FLOODFILE(:,13)=num2cell(F13(:));
FLOODFILE(:,14)=F14(:);
FLOODFILE(:,15)=F15(:);
```

```
%=F1 means a cell array,=num2cell means a number originally convert to cell

    fileID = fopen('FLOODFILE.dat','w');
    %gives file name for output but leave .dat
    formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f %s %s\n';

    [nrows,ncols] = size(FLOODFILE);

    HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s %s %s\n';

HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',..
.
        'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
        'DamageThen','Adjusted(2014)DamageNow','Narrative','Narrative2'};
    fprintf(fileID,HformatSpec,HEADER{1,:});

for row = 1:nrows
    fprintf(fileID,formatSpec,FLOODFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file

FindFlashFlood=strcmpi(EVENT_TYPE,'Flash Flood');

FF1=MONTH_NAME(FindFlashFlood>0);
FF2=YEAR(FindFlashFlood>0);
FF3=BEGIN_YEARMONTH(FindFlashFlood>0);
FF4=BEGIN_DAY(FindFlashFlood>0);
```

```
FF5=END_YEARMONTH(FindFlashFlood>0);
FF6=END_DAY(FindFlashFlood>0);
FF7=UEPISODEID(FindFlashFlood>0);
FF8=STATE(FindFlashFlood>0);
FF8=strrep(FF8,' ',");
FF9=EVENT_TYPE(FindFlashFlood>0);
FF9=strrep(FF9,' ',");
FF10=INJURIES(FindFlashFlood>0);
FF11=FATALITIES(FindFlashFlood>0);
FF12=DAMAGETHEN(FindFlashFlood>0);
FF13=ADJUSTEDDAMAGENOW(FindFlashFlood>0);
FF14=NARRATIVE(FindFlashFlood>0);
FF15=NARRATIVE2(FindFlashFlood>0);
%each of the different variables we want in our output


FLASHFLOODFILE=cell(length(FF1),15);
%filename=cell(length(FF#),columns)


FLASHFLOODFILE(:,1)=FF1(:);
FLASHFLOODFILE(:,2)=num2cell(FF2(:));
FLASHFLOODFILE(:,3)=num2cell(FF3(:));
FLASHFLOODFILE(:,4)=num2cell(FF4(:));
FLASHFLOODFILE(:,5)=num2cell(FF5(:));
FLASHFLOODFILE(:,6)=num2cell(FF6(:));
FLASHFLOODFILE(:,7)=num2cell(FF7(:));
FLASHFLOODFILE(:,8)=FF8(:);
FLASHFLOODFILE(:,9)=FF9(:);
```

```
FLASHFLOODFILE(:,10)=num2cell(FF10(:));
FLASHFLOODFILE(:,11)=num2cell(FF11(:));
FLASHFLOODFILE(:,12)=num2cell(FF12(:));
FLASHFLOODFILE(:,13)=num2cell(FF13(:));
FLASHFLOODFILE(:,14)=FF14(:);
FLASHFLOODFILE(:,15)=FF15(:);
%=FF1 means a cell array,=num2cell means a number originally convert to cell

   fileID = fopen('FLASHFLOODFILE.dat','w');
   %gives file name for output but leave .dat
   formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f %s %s\n';
   %fprintf in help to see different values

   [nrows,ncols] = size(FLASHFLOODFILE);

   HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s %s %s\n';

HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',..
.
      'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
      'DamageThen','Adjusted(2014)DamageNow','Narrative','Narrative2'};
   fprintf(fileID,HformatSpec,HEADER{1,:});

for row = 1:nrows
   fprintf(fileID,formatSpec,FLASHFLOODFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file
```

```
FindCoastalFlood=strcmpi(EVENT_TYPE,'Coastal Flood');

CF1=MONTH_NAME(FindCoastalFlood>0);
CF2=YEAR(FindCoastalFlood>0);
CF3=BEGIN_YEARMONTH(FindCoastalFlood>0);
CF4=BEGIN_DAY(FindCoastalFlood>0);
CF5=END_YEARMONTH(FindCoastalFlood>0);
CF6=END_DAY(FindCoastalFlood>0);
CF7=UEPISODEID(FindCoastalFlood>0);
CF8=STATE(FindCoastalFlood>0);
CF8=strrep(CF8,' ','');
CF9=EVENT_TYPE(FindCoastalFlood>0);
CF9=strrep(CF9,' ','');
CF10=INJURIES(FindCoastalFlood>0);
CF11=FATALITIES(FindCoastalFlood>0);
CF12=DAMAGETHEN(FindCoastalFlood>0);
CF13=ADJUSTEDDAMAGENOW(FindCoastalFlood>0);
CF14=NARRATIVE(FindCoastalFlood>0);
CF15=NARRATIVE2(FindCoastalFlood>0);
%each of the different variables we want in our output

COASTALFLOODFILE=cell(length(CF1),15);
%filename=cell(length(CF#),columns)

COASTALFLOODFILE(:,1)=CF1(:);
COASTALFLOODFILE(:,2)=num2cell(CF2(:));
```

```
COASTALFLOODFILE(:,3)=num2cell(CF3(:));
COASTALFLOODFILE(:,4)=num2cell(CF4(:));
COASTALFLOODFILE(:,5)=num2cell(CF5(:));
COASTALFLOODFILE(:,6)=num2cell(CF6(:));
COASTALFLOODFILE(:,7)=num2cell(CF7(:));
COASTALFLOODFILE(:,8)=CF8(:);
COASTALFLOODFILE(:,9)=CF9(:);
COASTALFLOODFILE(:,10)=num2cell(CF10(:));
COASTALFLOODFILE(:,11)=num2cell(CF11(:));
COASTALFLOODFILE(:,12)=num2cell(CF12(:));
COASTALFLOODFILE(:,13)=num2cell(CF13(:));
COASTALFLOODFILE(:,14)=CF14(:);
COASTALFLOODFILE(:,15)=CF15(:);
%=CF1 means a cell array,=num2cell means a number originally convert to cell

  fileID = fopen('COASTALFLOODFILE.dat','w');
  %gives file name for output but leave .dat
  formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f %s %s\n';
  %fprintf in help to see different values

  [nrows,ncols] = size(COASTALFLOODFILE);

  HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s %s %s\n';

HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',...
    'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
    'DamageThen','Adjusted(2014)DamageNow','Narrative','Narrative2'};
```

```
    fprintf(fileID,HformatSpec,HEADER{1,:});

for row = 1:nrows
    fprintf(fileID,formatSpec,COASTALFLOODFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file

FindMarineFlood=strcmpi(EVENT_TYPE,'Marine Flood');

MF1=MONTH_NAME(FindMarineFlood>0);
MF2=YEAR(FindMarineFlood>0);
MF3=BEGIN_YEARMONTH(FindMarineFlood>0);
MF4=BEGIN_DAY(FindMarineFlood>0);
MF5=END_YEARMONTH(FindMarineFlood>0);
MF6=END_DAY(FindMarineFlood>0);
MF7=UEPISODEID(FindMarineFlood>0);
MF8=STATE(FindMarineFlood>0);
MF8=strrep(MF8,' ','');
MF9=EVENT_TYPE(FindMarineFlood>0);
MF9=strrep(MF9,' ','');
MF10=INJURIES(FindMarineFlood>0);
MF11=FATALITIES(FindMarineFlood>0);
MF12=DAMAGETHEN(FindMarineFlood>0);
MF13=ADJUSTEDDAMAGENOW(FindMarineFlood>0);
MF14=NARRATIVE(FindMarineFlood>0);
MF15=NARRATIVE2(FindMarineFlood>0);
```

```
%each of the different variables we want in our output

MARINEFLOODFILE=cell(length(MF1),15);
%filename=cell(length(MF#),columns)

MARINEFLOODFILE(:,1)=MF1(:);
MARINEFLOODFILE(:,2)=num2cell(MF2(:));
MARINEFLOODFILE(:,3)=num2cell(MF3(:));
MARINEFLOODFILE(:,4)=num2cell(MF4(:));
MARINEFLOODFILE(:,5)=num2cell(MF5(:));
MARINEFLOODFILE(:,6)=num2cell(MF6(:));
MARINEFLOODFILE(:,7)=num2cell(MF7(:));
MARINEFLOODFILE(:,8)=MF8(:);
MARINEFLOODFILE(:,9)=MF9(:);
MARINEFLOODFILE(:,10)=num2cell(MF10(:));
MARINEFLOODFILE(:,11)=num2cell(MF11(:));
MARINEFLOODFILE(:,12)=num2cell(MF12(:));
MARINEFLOODFILE(:,13)=num2cell(MF13(:));
MARINEFLOODFILE(:,14)=MF14(:);
MARINEFLOODFILE(:,15)=MF15(:);
%=MF1 means a cell array,=num2cell means a number originally convert to cell

  fileID = fopen('MARINEFLOODFILE.dat','w');
  %gives file name for output but leave .dat
  formatSpec = '%s %d %d %d %d %d %d %s %s %d %d %f %f %s %s\n';
  %fprintf in help to see different values
```

```
    [nrows,ncols] = size(MARINEFLOODFILE);

    HformatSpec = '%s %s %s %s %s %s %s %s %s %s %s %s %s %s %s\n';

HEADER={'MonthName','Year','BeginYearMonth','BeginDay','EndYearMonth',..
.
        'EndDay','UEpisodeID','State','EventType','Injuries','Fatalities',...
        'DamageThen','Adjusted(2014)DamageNow','Narrative','Narrative2'};
    fprintf(fileID,HformatSpec,HEADER{1,:});

for row = 1:nrows
    fprintf(fileID,formatSpec,MARINEFLOODFILE{row,:});
end
fclose(fileID);
%program code to give output in a file that we can turn into excel file

finish3=[3]
```

Output of Matlab code is data sorted into individual disaster types for tornadoes, hurricanes, and floods. Other disater types (tsunamis, blizzards, hail, high winds, avalanches, and others) are removed by the MATLAB program. Earthquake data is already separated into individual events through NOAA National Center for Environmental Information database.

Hurricanes: Combine separate listings to create each event using NOAA National Hurricane Center Tropical Cyclone Reports, as well as information (month, begin and end day, year) from NOAA National Center for Environmental Information Storm Events

Database-Bulk Data Download files. Compare monetary and fatality values to ensure quality data; when needed, edit data based on information provided from both sets of reports. Example: Hurricane Katrina in 2005 is listed multiple times, this is for the reason that it struck many counties and states, so this data needed to be combined and values cross-referenced to ensure accuracy.

Earthquakes: Already grouped by event, adjust the monetary values to equate them to 2014 USD. For data that is a general value (Example: $50-$500 economic loss or 1-10 fatalities), the middle value ($225 or 5) is used, to not skew the output data.

Tornadoes: Already grouped by event, but adjustments to monetary values must be done to equate them to 2014USD.

Floods: This data set was the most difficult to group into individual events, due to the lack of labeling data byevent by NOAA National Weather Service (cited by the County Warning Area, then by the county and state policy, which leaves many events missing critical pieces of information). Example: If there is a flood that occurs in Ohio, then trickles down to the Mississippi River; it is reported as separate events (in each County Warning Area) due to the lack of communication and identification by NOAA National Weather Service. There are many none combined events that need to be combined to form an event. This study found that using the FEMA Disaster Declarations website would help with this effort, but it still left many pieces of an event out. In this case, it was agreed to combine the data by state and then by month to get the best result for floods.

APPENDIX B

Step-by-Step Process followed to Analyze Data

This appendix will take the resultant Excel files that were created at the end of Appendix A, and turn them into graphical representations for analysis. Each natural disaster workbook will expand to contain all the data and graphs needed to complete this study. The different worksheets and graphs will show cumulative and non-cumulative techniques in order to determine the best possible outcome, as well as if they follow power function distributions allowing for probabilistic forecasting of new larger events. Then, this study will combine the data sets into one composite graph for each, economic loss and fatalities, to understand which natural disasters are related in terms of their frequency and return period.

1. Using combined results and Excel, create new worksheets to graph results.
    - 1.1. Sort the Adjusted (2014) Damage Now or Fatalities column from largest to smallest.
    - 1.2. Open a new worksheet (label Economic Loss Values or Fatalities Values) in the Excel file for each of the hazards (tornadoes, floods, hurricanes, and earthquakes).
    - 1.3. Paste the Adjusted (2014) Damage Now or Fatalities column into column D (label Multiples) of the Economic Loss Values or Fatalities Values worksheet.

1.4. Rank the values in column E (label Rank) from 1 (being the largest) to X (being the smallest). If using formulas to compute the entire column, make sure to copy and use paste special values only.

1.5. Copy and paste the Multiples values only in a new worksheet in order to remove multiples, since this study only looks at the cumulative number of events => X.

1.6. In the new sheet, choose the sort function once again. Sort the values in column A from smallest to largest, and the values in column B from largest to smallest.

1.7. Select all of column A, and then choose the filter (advanced) function.

1.8. In the filter function box, select the check box next to unique records only.

1.9. Copy and paste the values returned back into the Economic Loss Values or Fatalities Values worksheet into column A (label Singles) and the rank will be copied into column B (label Rank).

1.10. Using the sort function, sort Singles column from largest to smallest and Rank column from smallest to largest.

1.11. Remove any 0 values in the Rank column, since those do not pertain to this study and check the remaining values for accuracy.

2. Using the Multiples values, plot the data points on a marked scatter plot for visualization of where points are plotted.

2.1. Copy and paste the Multiples values and Rank into a new worksheet (label Economic Loss Rank Per Year or Fatalities Rank Per Year) in columns G (label Economic Loss or Fatalities) and H (label Rank).

2.2. For column F (label Multiples Date Range), the date range will need to be computed. Using the starting date and ending date calculate the range for each of the hazards.

2.3. Column I (label Rank Per Year = Rank/# Years), is the computation of column H/column F (Rank/Multiples Date Range). If using a formula to compute this step, copy and use paste special values at the end in order the correct values needed to make the graphs.

3. Using the Singles values, obtain the rank per year values needed for graphs.

3.1. Copy and paste the Singles values and Rank into the Economic Loss Rank Per Year or Fatalities Rank Per Year worksheet in columns B (label Economic Loss or Fatalities) and C (label Rank).

3.2. For column A (label Single Date Range), the date range will need to be computed. Using the starting date and ending date calculate the range for each of the hazards.

3.3. Column D (label Rank Per Year = Rank/# Years), is the computation of column C/column A (Rank/Single Date Range). If using a formula to compute this step, copy and use paste special values at the end in order the correct values needed to make the graphs.

4. Create graphs of cumulative number of events => X and cumulative number of events/year => X, using cumulative frequency techniques.

4.1. Using Excel, create marked scatter plots (move the actual chart to a new chart for better viewing) for separate analysis of data values.

4.2. Multiples: Add data from columns G (Economic Loss or Fatalities) and H (Rank) to a blank graph for cumulative number of events => X plot (label Economic Loss Plot or Fatalities Plot) and columns G (Economic Loss or Fatalities) and I (Rank Per Year = Rank/# Years) to another blank graph for the cumulative number of events/year => X plot (label Economic Loss Rank Per Year Plot or Fatalities Rank Per Year Plot).

4.3. Change the x-axis and y-axis to log scale to show the correct output for use with power law relationships.

4.4. Singles: Add (overlay) data from columns B (Economic Loss or Fatalities) and C (Rank) to the Economic Loss or Fatalities Plot for cumulative number of events => X plot and columns B (Economic Loss or Fatalities) and D (Rank Per Year = Rank/# Years) to the Economic Loss Rank Per Year Plot/Fatalities Rank Per Year Plot for the cumulative number of events/year => X plot.

4.5. Add a power function trendline to the overlay points and show the equation on the graph to see how the slope changes when values are added or removed to find the best-fit line or multiple lines if an inflection point exists.

5. Create graphs of cumulative number of events => X and cumulative number of events/year => X, using non-cumulative frequency techniques.

5.1. Open a new worksheet (label Economic Loss Histogram Values or Fatalities Histogram Values).

5.2. Copy the Multiples column of Economic Loss or Fatalities (column G) from the Economic Loss Rank Per Year or Fatalities Rank Per Year worksheet and paste into column A (label Economic Loss or Fatalities) of the Economic Loss Histogram Values or Fatalities Histogram Values worksheet.

5.3. For Binning purposes, use the Series function under the Fill option on the Excel workbook Home tab.

  5.3.1. Column B will be your Series (label Economic Loss or Fatalities), enter 0 into the second row.

  5.3.2. Select the Series function and enter a step value and the stop value for your data set. This will automatically generate a series for use with the histogram.

5.4. To create a histogram, select the Data Tab and then the Data Analysis function.

  5.4.1. Select the Histogram feature from the Analysis Tools menu and click OK.

  5.4.2. Input box: Input Range will be column A and Bin Range will be column B.

  5.4.3. Select the Labels box since the worksheet has labels to start the columns.

  5.4.4. Output options: Output Range select column D and check the box next to Chart Output.

  5.4.5. Click OK.

5.4.6. Move the chart to a New Sheet (label Economic Loss Histogram or Fatalities Histogram).

5.4.7. If the histogram needs to be edited for a better outcome, repeat this process starting at Part c of this section using a different step value in the binning process.

5.5. Copy and paste the Economic Loss or Frequency values from columns D and E into columns G and H. Then create a Frequency/Year column in column I by taking the Frequency values and dividing them by the number of Years in column A of the Economic Loss Rank Per Year or Fatalities Rank Per Year worksheet.

5.6. Add columns G (Economic Loss or Fatalities) and H (Frequency) from the Economic Loss Histogram Values or Fatalities Histogram Values to the Economic Loss Plot or Fatalities Plot. Add a Power function trendline to the data set and show the equation on the graph.

5.7. Add columns G (Economic Loss or Fatalities) and I (Frequency/Year) from the Economic Loss Histogram Values or Fatalities Histogram Values to the Economic Loss Plot Per Year or Fatalities Plot Per Year. Add a Power function trendline to the data set and show the equation on the graph.

5.8. Pick the largest data points from column H (Frequency) and copy columns G, H, and I for that point to paste into columns K, L, and M respectively; add the same column headers in the first row.

5.9. Overlay these points onto the Economic Loss Plot Per Year or Fatalities Plot Per Year. Add a Power function trendline to the data set and show the equation on the graph.

6. Create graphs of cumulative number of events per year => X, with return period.

6.1. Repeat steps 2 through 4 in a new Excel workbook, creating separate worksheets for each of the individual disaster types.

6.2. Create an empty set of economic/fatality values and rank per year values in another worksheet (label empty set) in order to create the return period axis (secondary axis).

6.3. Add all of the data sets (hurricanes, tornadoes, floods, and earthquakes) to a new marked scatterplot graph following the process of step 4. The empty set data set will be added to the scatterplot, but will need to be edited to the secondary axis and then represented by no marker so they do not show in the final graphical output.

6.4. When the secondary axis is shown it will need to be formatted to the inverse of the primary axis to show the proper return period.

APPENDIX C:

Hurricane and Earthquake Data Sets

The following tables provide detailed information for events related to hurricanes and earthquakes. Hurricane tables show the differences between the data obtained from NOAA National Center for Environmental Information website (C.1 (page 90)) and the combined data once processed through the Matlab computer program (C.2 (page 95)). Hurricane data set required combining events based on time of occurrence but did not complete the data. In this case, NOAA National Hurricane Center Tropical Cyclone Reports were used for all data. Earthquake tables show data obtained from NOAA National Center for Environmental Information website (C.3 (page 98)) and the hand-edited final version (C.4 (page 104)) for use with Appendix B. Table C.4 provides results of economic loss and fatalities with the incorporated description/generic values from table C.3. Referring back to Section 2.3, the generic values will be represented by using the middle value as to not skew the output plots.

Table C.1: Hurricane data (sorted by date) after processing by Matlab computer program. Output data includes: year, date, episode id (main event id), state, event type, fatalities, economic loss at time of event, economic loss adjusted to 2014USD.

Begin Year Month	Begin Day	UEpisode ID	Baker Event ID Number	State	Event Type	Fatalities	Damage (dollars of the day)	Adjusted (2014) Damage Now
199607	10	1049285	1	FLORIDA	Hurricane(Typhoon)	0	0	0
199607	10	1049286	1	FLORIDA	Hurricane(Typhoon)	0	0	0
199607	10	1049287	1	FLORIDA	Hurricane(Typhoon)	2	0	0
199607	11	1033180	1	GEORGIA	Hurricane(Typhoon)	0	0	0
199607	11	1055886	1	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199607	12	1044586	1	NORTHCAROLINA	Hurricane(Typhoon)	1	267250000	403547500
199607	12	1045250	1	NORTHCAROLINA	Hurricane(Typhoon)	0	230000	347300
199607	12	1046244	1	NORTHCAROLINA	Hurricane(Typhoon)	0	0	0
199607	12	1057163	1	NORTHCAROLINA	Hurricane(Typhoon)	0	19000000	28690000
199607	12	1057164	1	NORTHCAROLINA	Hurricane(Typhoon)	0	14500000	21895000
199607	12	1402892	1	NORTHCAROLINA	Hurricane(Typhoon)	0	11000000	16610000
199607	12	1039943	1	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199607	12	1055887	1	SOUTHCAROLINA	Hurricane(Typhoon)	0	780000	1177800
199607	12	1055888	1	SOUTHCAROLINA	Hurricane(Typhoon)	0	1300000	1963000
199607	12	1055789	1	VIRGINIA	Hurricane(Typhoon)	0	0	0
199607	13	1054465	1	MARYLAND	Hurricane(Typhoon)	0	115000	173650
199608	29	1056102		NORTHCAROLINA	Hurricane(Typhoon)	0	0	0
199608	31	1055256		SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199609	2	1403446		FLORIDA	Hurricane(Typhoon)	0	0	0
199609	2	1044845		MAINE	Hurricane(Typhoon)	0	0	0
199609	2	1048803		NEWHAMPSHIRE	Hurricane(Typhoon)	0	0	0
199609	4	1045259	2	NORTHCAROLINA	Hurricane(Typhoon)	4	792150000	1196146500
199609	5	1045440	2	NORTHCAROLINA	Hurricane(Typhoon)	7	0	0
199609	5	1046467	2	NORTHCAROLINA	Hurricane(Typhoon)	0	1000000	1510000
199609	5	1048167	2	NORTHCAROLINA	Hurricane(Typhoon)	2	226000000	341260000
199609	5	1048176	2	NORTHCAROLINA	Hurricane(Typhoon)	0	201000000	303510000
199609	5	1048254	2	NORTHCAROLINA	Hurricane(Typhoon)	0	7000000	10570000
199609	5	1047271	2	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199609	5	1048994	2	SOUTHCAROLINA	Hurricane(Typhoon)	1	20800000	31408000
199609	5	1057010	2	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199609	5	1048707	2	VIRGINIA	Hurricane(Typhoon)	0	0	0
199609	6	1045721	2	MARYLAND	Hurricane(Typhoon)	0	1000000	1510000
199707	17	38549	3	LOUISIANA	Hurricane(Typhoon)	0	5000000	7350000
199707	17	49809	3	MISSISSIPPI	Hurricane(Typhoon)	0	0	0

199707	21	1057729	3	ALABAMA	Hurricane(Typhoon)	1	63000000	92610000
199808	26	55939	4	NORTHCAROLINA	Hurricane(Typhoon)	1	13400000	19430000
199808	26	67944	4	NORTHCAROLINA	Hurricane(Typhoon)	0	99000000	143550000
199808	26	1077715	4	NORTHCAROLINA	Hurricane(Typhoon)	0	123400000	178930000
199808	26	1082856	4	NORTHCAROLINA	Hurricane(Typhoon)	0	17100000	24795000
199808	26	1082857	4	NORTHCAROLINA	Hurricane(Typhoon)	0	26200000	37990000
199808	26	1081841	4	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199808	26	1149000	4	SOUTHCAROLINA	Hurricane(Typhoon)	0	3800000	5510000
199808	26	65274	4	VIRGINIA	Hurricane(Typhoon)	0	26659000	38655550
199808	27	1079545	4	NORTHCAROLINA	Hurricane(Typhoon)	0	50000000	72500000
199809	1	1083868	5	ALABAMA	Hurricane(Typhoon)	0	10000	14500
199809	1	1150649	5	FLORIDA	Hurricane(Typhoon)	0	150000	217500
199809	1	65261	5	LOUISIANA	Hurricane(Typhoon)	0	32000	46400
199809	1	1072977		TEXAS	Hurricane(Typhoon)	0	10000	14500
199809	2	60747	5	FLORIDA	Hurricane(Typhoon)	0	1130000	1638500
199809	2	61197	5	FLORIDA	Hurricane(Typhoon)	2	5995000	8692750
199809	25	1149148	6	ALABAMA	Hurricane(Typhoon)	1	179164000	259787800
199809	25	61980	6	FLORIDA	Hurricane(Typhoon)	0	270000000	391500000
199809	25	64390	6	FLORIDA	Hurricane(Typhoon)	0	250000	362500
199809	25	1149147	6	FLORIDA	Hurricane(Typhoon)	0	135000000	195750000
199809	25	1150605	6	FLORIDA	Hurricane(Typhoon)	0	0	0
199809	25	1073878	6	MISSISSIPPI	Hurricane(Typhoon)	0	72000000	104400000
199809	26	1072033	6	LOUISIANA	Hurricane(Typhoon)	0	0	0
199809	27	65438	6	LOUISIANA	Hurricane(Typhoon)	0	30060000	43587000
199809	27	65477	6	MISSISSIPPI	Hurricane(Typhoon)	0	602000000	872900000
199809	28	68612	6	FLORIDA	Hurricane(Typhoon)	0	61975000	89863750
199908	29	1406826	6	FLORIDA	Hurricane(Typhoon)	1	100000	142000
199908	30	1405652	7	NORTHCAROLINA	Hurricane(Typhoon)	0	0	0
199908	30	1406733	7	NORTHCAROLINA	Hurricane(Typhoon)	0	75000	106500
199908	30	1406332	7	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
199909	1	1408227	7	NORTHCAROLINA	Hurricane(Typhoon)	0	35000	49700
199909	1	1408221	7	VIRGINIA	Hurricane(Typhoon)	0	27000	38340
199909	4	77641	7	NORTHCAROLINA	Hurricane(Typhoon)	0	3000000	4260000
199909	13	1405397	8	FLORIDA	Hurricane(Typhoon)	0	100000	142000
199909	14	501382	8	FLORIDA	Hurricane(Typhoon)	0	20000	28400
199909	14	502888	8	NORTHCAROLINA	Hurricane(Typhoon)	13	824224000	1170398080
199909	15	77998	8	FLORIDA	Hurricane(Typhoon)	0	2500000	3550000
199909	15	79215	8	FLORIDA	Hurricane(Typhoon)	0	1000000	1420000
199909	15	1405090	8	FLORIDA	Hurricane(Typhoon)	0	61000000	86620000

199909	15	1406050	8	FLORIDA	Hurricane(Typhoon)	0	3000000	4260000
199909	15	1413083	8	FLORIDA	Hurricane(Typhoon)	0	60000	85200
199909	15	502540		GEORGIA	Hurricane(Typhoon)	0	0	0
199909	15	1408884	9	MARYLAND	Hurricane(Typhoon)	0	853000	1211260
199909	15	77757	9	NORTHCAROLINA	Hurricane(Typhoon)	0	3500000000	4970000000
199909	15	1408624	9	NORTHCAROLINA	Hurricane(Typhoon)	0	75395000	107060900
199909	15	502707	9	SOUTHCAROLINA	Hurricane(Typhoon)	0	17000000	24140000
199909	15	1407890	9	VIRGINIA	Hurricane(Typhoon)	1	141698000	201211160
199910	14	77474	10	FLORIDA	Hurricane(Typhoon)	0	600000000	852000000
199910	15	1405611	10	FLORIDA	Hurricane(Typhoon)	0	51000000	72420000
199910	15	1410013	10	FLORIDA	Hurricane(Typhoon)	0	0	0
199910	16	1406478	10	FLORIDA	Hurricane(Typhoon)	0	600000	852000
199910	16	1406479	10	FLORIDA	Hurricane(Typhoon)	0	300000	426000
199910	16	1415740	10	FLORIDA	Hurricane(Typhoon)	0	300000	426000
199910	16	1409248	10	NORTHCAROLINA	Hurricane(Typhoon)	1	0	0
199910	17	1408011	10	NORTHCAROLINA	Hurricane(Typhoon)	0	31000	44020
199910	17	77866	10	VIRGINIA	Hurricane(Typhoon)	0	45000	63900
200009	17	98208	11	FLORIDA	Hurricane(Typhoon)	0	0	0
200009	17	101916	11	FLORIDA	Hurricane(Typhoon)	0	5050000	6918500
200111	5	124577	12	FLORIDA	Hurricane(Typhoon)	0	50000	67000
200111	5	124776	12	FLORIDA	Hurricane(Typhoon)	0	0	0
200210	2	145212	13	ALABAMA	Hurricane(Typhoon)	0	175000	231000
200210	2	132025	13	LOUISIANA	Hurricane(Typhoon)	0	149655000	197544600
200210	3	131105	13	LOUISIANA	Hurricane(Typhoon)	0	1000000	1320000
200210	3	145529	13	LOUISIANA	Hurricane(Typhoon)	0	536000000	707520000
200210	3	131080	13	MISSISSIPPI	Hurricane(Typhoon)	0	522510	689713.2
200307	14	163783	14	TEXAS	Hurricane(Typhoon)	0	10880300	14035587
200307	15	161365	14	TEXAS	Hurricane(Typhoon)	0	0	0
200309	17	150474	15	NORTHCAROLINA	Hurricane(Typhoon)	0	449850000	580306500
200309	18	150642	15	NORTHCAROLINA	Hurricane(Typhoon)	1	7293000	9407970
200309	18	161857	15	NORTHCAROLINA	Hurricane(Typhoon)	0	3900000	5031000
200309	18	162575	15	NORTHCAROLINA	Hurricane(Typhoon)	1	16899000	21799710
200309	18	162959	15	VIRGINIA	Hurricane(Typhoon)	2	9700000	12513000
200309	18	162984	15	VIRGINIA	Hurricane(Typhoon)	2	516921000	666828090
200408	3	179939	16	NORTHCAROLINA	Hurricane(Typhoon)	0	7550000	9437500
200408	11	180401	17	FLORIDA	Hurricane(Typhoon)	0	160000	200000
200408	13	176754	17	FLORIDA	Hurricane(Typhoon)	0	20000	25000
200408	13	177442	17	FLORIDA	Hurricane(Typhoon)	0	2575000	3218750
200408	13	179346	17	FLORIDA	Hurricane(Typhoon)	7	5707600000	7134500000

200408	13	180244	17	FLORIDA	Hurricane(Typhoon)	0	0	0
200408	13	181737	17	FLORIDA	Hurricane(Typhoon)	2	52000000	65000000
200408	14	178910	17	NORTHCAROLINA	Hurricane(Typhoon)	0	9835000	12293750
200408	14	179094	17	NORTHCAROLINA	Hurricane(Typhoon)	0	12925000	16156250
200408	14	178378	17	SOUTHCAROLINA	Hurricane(Typhoon)	0	6500000	8125000
200408	14	180685	17	SOUTHCAROLINA	Hurricane(Typhoon)	0	0	0
200409	1	179618	18	FLORIDA	Hurricane(Typhoon)	0	20000	25000
200409	4	180898	18	FLORIDA	Hurricane(Typhoon)	0	711000000	888750000
200409	4	182297	18	FLORIDA	Hurricane(Typhoon)	0	4923200000	6154000000
200409	12	180993		FLORIDA	Hurricane(Typhoon)	0	0	0
200409	13	180715	19	ALABAMA	Hurricane(Typhoon)	0	2525000000	3156250000
200409	13	180430	19	FLORIDA	Hurricane(Typhoon)	7	4025000000	5031250000
200409	14	179870	19	MISSISSIPPI	Hurricane(Typhoon)	0	200000	250000
200409	15	180860	19	FLORIDA	Hurricane(Typhoon)	6	90425000	113031250
200409	15	164633	19	LOUISIANA	Hurricane(Typhoon)	0	15840000	19800000
200409	15	165398	19	MISSISSIPPI	Hurricane(Typhoon)	0	10000000	12500000
200409	16	179404	19	MISSISSIPPI	Hurricane(Typhoon)	1	2000800	2501000
200409	24	179336	20	FLORIDA	Hurricane(Typhoon)	0	5000	6250
200409	25	181099	20	FLORIDA	Hurricane(Typhoon)	0	353000000	441250000
200409	25	181902	20	FLORIDA	Hurricane(Typhoon)	0	388600000	485750000
200507	5	195219	21	LOUISIANA	Hurricane(Typhoon)	0	47500000	57475000
200507	8	189802	21	FLORIDA	Hurricane(Typhoon)	1	0	0
200507	8	198227	21	FLORIDA	Hurricane(Typhoon)	1	7150000	8651500
200507	9	193751	21	ALABAMA	Hurricane(Typhoon)	0	120100000	145321000
200507	9	194470	21	ALABAMA	Hurricane(Typhoon)	0	1500000	1815000
200507	9	192507	21	FLORIDA	Hurricane(Typhoon)	0	62000000	75020000
200507	9	194727	21	FLORIDA	Hurricane(Typhoon)	0	1500300000	1815363000
200507	9	193150	21	GEORGIA	Hurricane(Typhoon)	0	7700000	9317000
200507	10	194726	21	ALABAMA	Hurricane(Typhoon)	0	0	0
200507	10	194781	21	ALABAMA	Hurricane(Typhoon)	0	0	0
200507	10	194782	21	ALABAMA	Hurricane(Typhoon)	0	0	0
200507	10	193672	21	FLORIDA	Hurricane(Typhoon)	0	0	0
200507	10	195570	21	FLORIDA	Hurricane(Typhoon)	0	0	0
200507	10	194219	21	GEORGIA	Hurricane(Typhoon)	0	0	0
200507	10	194167	21	MISSISSIPPI	Hurricane(Typhoon)	0	4700000	5687000
200508	25	197140	22	FLORIDA	Hurricane(Typhoon)	6	523000000	632830000
200508	26	198895	22	FLORIDA	Hurricane(Typhoon)	0	6900000	8349000
200508	27	196557	22	ALABAMA	Hurricane(Typhoon)	0	1000000000	1210000000
200508	27	196558	22	MISSISSIPPI	Hurricane(Typhoon)	0	250000000	302500000

200508	28	197162	22	FLORIDA	Hurricane(Typhoon)	0	1700000	2057000
200508	28	197919	22	LOUISIANA	Hurricane(Typhoon)	0	16929400000	20484574000
200508	28	197962	22	MISSISSIPPI	Hurricane(Typhoon)	0	7347400000	8890354000
200508	29	196782	22	ARKANSAS	Hurricane(Typhoon)	0	7400000	8954000
200508	29	197878	22	GEORGIA	Hurricane(Typhoon)	0	0	0
200508	29	196079	22	LOUISIANA	Hurricane(Typhoon)	0	30000	36300
200508	29	196783	22	LOUISIANA	Hurricane(Typhoon)	0	52600000	63646000
200508	29	196674	22	MISSISSIPPI	Hurricane(Typhoon)	15	7390300000	8942263000
200508	29	198064	22	MISSISSIPPI	Hurricane(Typhoon)	0	0	0
200508	29	198119	22	MISSISSIPPI	Hurricane(Typhoon)	0	0	0
200508	29	198762	22	MISSISSIPPI	Hurricane(Typhoon)	0	0	0
200509	13	199692	23	NORTHCAROLINA	Hurricane(Typhoon)	0	53660000	64928600
200509	14	202516	23	NORTHCAROLINA	Hurricane(Typhoon)	0	8300000	10043000
200509	20	198740	24	FLORIDA	Hurricane(Typhoon)	0	0	0
200509	23	197953	24	LOUISIANA	Hurricane(Typhoon)	1	3995000000	4833950000
200509	23	197860	24	TEXAS	Hurricane(Typhoon)	1	2090000000	2528900000
200509	23	202518	24	TEXAS	Hurricane(Typhoon)	3	159500000	192995000
200509	24	202338	24	ARKANSAS	Hurricane(Typhoon)	0	1050000	1270500
200509	24	200034	24	LOUISIANA	Hurricane(Typhoon)	0	0	0
200509	24	202337	24	LOUISIANA	Hurricane(Typhoon)	0	8750000	10587500
200509	24	202508	24	MISSISSIPPI	Hurricane(Typhoon)	0	2815000	3406150
200509	24	200236	24	TEXAS	Hurricane(Typhoon)	1	0	0
200510	23	200716	25	FLORIDA	Hurricane(Typhoon)	0	99000000	119790000
200510	24	199545	25	FLORIDA	Hurricane(Typhoon)	0	101000000	122210000
200510	24	202552	25	FLORIDA	Hurricane(Typhoon)	5	10000000000	12100000000
200709	12	11848	26	TEXAS	Hurricane(Typhoon)	0	3000000	3420000
200709	14	11335	26	GEORGIA	Hurricane(Typhoon)	0	0	0
200809	1	24573	27	MISSISSIPPI	Hurricane(Typhoon)	0	21890000	24079000
200809	12	24718	28	TEXAS	Hurricane(Typhoon)	1	1348000000	1482800000
201108	27	55738	29	NORTHCAROLINA	Hurricane(Typhoon)	0	3500000	3675000
201208	28	66547	30	LOUISIANA	Hurricane(Typhoon)	3	728900000	750767000

Table C.2: Hurricane data after combination of pieces of each event into the individual events. Output data provides important information including: year, date, episode id, state, event type, fatalities, economic loss at time of event, economic loss adjusted to 2014USD.

Begin Year Month	Begin Day	UEpisode ID	State	Event Type	Fatalities	Damage Then	Adjusted (2014) Damage Now
195008	30		ALABAMA	Hurricane(Typhoon)	1	2550000	25041000
195009	5		FLORIDA	Hurricane(Typhoon)	2	3300000	32406000
195010	17		FLORIDA	Hurricane(Typhoon)	4	28000000	274960000
195208	30		SOUTHCAROLINA	Hurricane(Typhoon)	3	2750000	24557500
195308	13		NORTHCAROLINA	Hurricane(Typhoon)	1	1000000	8870000
195309	26		FLORIDA	Hurricane(Typhoon)	0	200000	1774000
195408	26		NEWYORK	Hurricane(Typhoon)	60	461000000	4056800000
195409	11		MASSACHUSETTS	Hurricane(Typhoon)	20	40000000	352000000
195410	15		NORTHCAROLINA	Hurricane(Typhoon)	95	281000000	2472800000
195508	17		NORTHCAROLINA	Hurricane(Typhoon)	184	832000000	7346560000
195508	12		NORTHCAROLINA	Hurricane(Typhoon)	0	40000000	353200000
195509	19		NORTHCAROLINA	Hurricane(Typhoon)	7	88035000	777349050
195609	24		LOUISIANA	Hurricane(Typhoon)	15	24874000	216403800
195706	27		TEXAS	Hurricane(Typhoon)	455	150000000	1263000000
195907	8		SOUTHCAROLINA	Hurricane(Typhoon)	1	75000	610500
195907	24		TEXAS	Hurricane(Typhoon)	0	7000000	56980000
195909	29		SOUTHCAROLINA	Hurricane(Typhoon)	22	14000000	113960000
196009	10		FLORIDA	Hurricane(Typhoon)	50	386500000	3092000000
196009	14		MISSISSIPPI	Hurricane(Typhoon)	0	1060000	8480000
196109	11		TEXAS	Hurricane(Typhoon)	46	325000000	2574000000
196309	17		TEXAS	Hurricane(Typhoon)	3	12560000	97214400
196408	27		FLORIDA	Hurricane(Typhoon)	3	128500000	981740000
196409	10		FLORIDA	Hurricane(Typhoon)	5	250000000	1910000000
196410	3		LOUISIANA	Hurricane(Typhoon)	38	125000000	955000000
196410	14		FLORIDA	Hurricane(Typhoon)	3	10000000	76400000
196509	6		FLORIDA	Hurricane(Typhoon)	75	1419800000	10676896000
196606	8		FLORIDA	Hurricane(Typhoon)	6	10050000	73465500
196709	20		TEXAS	Hurricane(Typhoon)	15	200000000	1418000000
196810	19		FLORIDA	Hurricane(Typhoon)	3	6700000	45560000
196908	17		MISSISSIPPI	Hurricane(Typhoon)	256	1420750000	9163837500
196909	9		MAINE	Hurricane(Typhoon)	0	0	0
197008	3		TEXAS	Hurricane(Typhoon)	11	453700000	2767570000
197109	10		TEXAS	Hurricane(Typhoon)	2	30230000	176845500

197109	16		LOUISIANA	Hurricane(Typhoon)	0	25000000	146250000
197109	30		NORTHCAROLINA	Hurricane(Typhoon)	0	10000000	58500000
197206	19		FLORIDA	Hurricane(Typhoon)	120	3100000000	17546000000
197409	8		LOUISIANA	Hurricane(Typhoon)	1	150000000	720000000
197509	23		FLORIDA	Hurricane(Typhoon)	21	500000000	2200000000
197608	10		NEWYORK	Hurricane(Typhoon)	5	100000000	416000000
197709	5		LOUISIANA	Hurricane(Typhoon)	0	10000000	39100000
197907	11		LOUISIANA	Hurricane(Typhoon)	1	20000000	65200000
197909	3		FLORIDA	Hurricane(Typhoon)	15	320000000	1043200000
197909	13		ALABAMA	Hurricane(Typhoon)	5	2300000000	7498000000
198008	10		TEXAS	Hurricane(Typhoon)	2	300000000	861000000
198408	17		TEXAS	Hurricane(Typhoon)	21	2000000000	4560000000
198409	13		NORTHCAROLINA	Hurricane(Typhoon)	3	65000000	148200000
198507	24		SOUTHCAROLINA	Hurricane(Typhoon)	1	0	0
198508	15		LOUISIANA	Hurricane(Typhoon)	1	100000000	220000000
198509	27		NORTHCAROLINA	Hurricane(Typhoon)	8	900000000	1980000000
198509	1		MISSISSIPPI	Hurricane(Typhoon)	4	1250000000	2750000000
198510	29		LOUISIANA	Hurricane(Typhoon)	12	1500000000	3300000000
198511	21		FLORIDA	Hurricane(Typhoon)	5	300000000	660000000
198606	26		TEXAS	Hurricane(Typhoon)	4	2000000	4320000
198608	17		NORTHCAROLINA	Hurricane(Typhoon)	0	400000	864000
198710	12		FLORIDA	Hurricane(Typhoon)	0	500000	1040000
198809	9		LOUISIANA	Hurricane(Typhoon)	1	2500000	5000000
198908	1		TEXAS	Hurricane(Typhoon)	13	100000000	191000000
198909	22		SOUTHCAROLINA	Hurricane(Typhoon)	21	10000000000	19100000000
198910	15		TEXAS	Hurricane(Typhoon)	3	70000000	133700000
199108	19		RHODEISLAND	Hurricane(Typhoon)	6	680000000	1183200000
199208	23		FLORIDA	Hurricane(Typhoon)	61	26001000000	43941690000
199508	2		FLORIDA	Hurricane(Typhoon)	3	700000000	1085000000
199510	4		FLORIDA	Hurricane(Typhoon)	13	5142000000	7970100000
199607	12		NORTHCAROLINA	Hurricane(Typhoon)	7	270000000	407700000
199609	6	1403446	NORTHCAROLINA	Hurricane(Typhoon)	34	3200000000	4832000000
199707	17	38549	LOUISIANA	Hurricane(Typhoon)	9	68000000	99960000
199808	26	55939	NORTHCAROLINA	Hurricane(Typhoon)	3	720000000	1044000000
199809	1	1083868	ALABAMA	Hurricane(Typhoon)	3	79000000	114550000
199809	25	1149148	ALABAMA	Hurricane(Typhoon)	1	6000000000	8700000000
199908	23		TEXAS	Hurricane(Typhoon)	0	60000000	85200000
199909	13	1405397	NORTHCAROLINA	Hurricane(Typhoon)	56	6900000000	9798000000
199910	15	77474	FLORIDA	Hurricane(Typhoon)	8	800000000	1136000000

200210	2	145212	ALABAMA	Hurricane(Typhoon)	2	925000000	1221000000
200307	14	163783	TEXAS	Hurricane(Typhoon)	3	180000000	232200000
200309	17	150474	NORTHCAROLINA	Hurricane(Typhoon)	50	5370000000	6927300000
200408	11	180401	FLORIDA	Hurricane(Typhoon)	35	15113000000	18891250000
200408	29		SOUTHCAROLINA	Hurricane(Typhoon)	9	130000000	162500000
200408	3	179939	NORTHCAROLINA	Hurricane(Typhoon)	1	7550000	9437500
200409	12	180993	FLORIDA	Hurricane(Typhoon)	57	18820000000	23525000000
200409	1	179618	FLORIDA	Hurricane(Typhoon)	48	9507000000	11883750000
200409	24	179336	FLORIDA	Hurricane(Typhoon)	4	7660000000	9575000000
200507	5	195219	LOUISIANA	Hurricane(Typhoon)	15	2545000000	3079450000
200507	5		LOUISIANA	Hurricane(Typhoon)	1	320000000	387200000
200508	29	198762	MISSISSIPPI	Hurricane(Typhoon)	1833	108000000000	130680000000
200509	20	198740	FLORIDA	Hurricane(Typhoon)	62	12037000000	14564770000
200509	13	199692	NORTHCAROLINA	Hurricane(Typhoon)	1	70000000	84700000
200510	23	200716	FLORIDA	Hurricane(Typhoon)	5	21007000000	25418470000
200709	12	11848	TEXAS	Hurricane(Typhoon)	1	3000000	3420000
200807	24		TEXAS	Hurricane(Typhoon)	1	1050000000	1155000000
200809	12	24718	TEXAS	Hurricane(Typhoon)	85	29520000000	32472000000
200809	1	24573	MISSISSIPPI	Hurricane(Typhoon)	52	4618000000	5079800000
201108	27	55738	NORTHCAROLINA	Hurricane(Typhoon)	41	15800000000	16590000000
201208	28	66547	LOUISIANA	Hurricane(Typhoon)	5	2350000000	2420500000
201407	3		NORTHCAROLINA	Hurricane(Typhoon)	0	4052000	4052000

Table C.3: Earthquake data by individual events. Output data provides important information including: year, month, day, hour, minute, second, magnitude, name, number of deaths, description of deaths, economic loss in millions, and description of economic loss (at time of event).

YEAR	MO	DY	HR	MIN	SEC	MAG	LOCATION_NAME	DTH	DES	DAM_MILL	DES
1900	10	9	12	25		8.3	ALASKA: KODIAK ISLAND				1
1900	8	11	4	40			SE. ALASKA				
1901	12	31	9	2	30	7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				1
1901	3	3	7	45		6.4	CALIFORNIA: SAN DIEGO				1
1902	4	29	6	57			CALIFORNIA: SOUTHERN				2
1902	1	1	5	20		7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
1903	6	2	13	17		8.3	ALASKA: SOUTHWEST				
1904	8	27	21	56		8.3	ALASKA: RAMPART				
1905	2	14	8	46		7.9	ALASKA: ANDREANOF ISLANDS				
1906	4	18	13	12	21	7.9	CALIFORNIA: SAN FRANCISCO	700	3	400	4
1906	8	17	0	10	42	7.8	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				
1906	12	23	17	22		7.6	ALASKA: ALEUTIAN ISLANDS				
1907	9	2	16	1		7.8	ALASKA: ALEUTIAN ISLANDS				
1907	9	24	12	59		5.5	ALASKA: SKAGWAY				
1908	2	14	11	25		6	ALASKA GULF				
1908	9	21	6	31		6.8	HAWAII				
1909	4	10	19	36		7.8	ALASKA: ALEUTIAN ISLANDS				
1911	9	22	5	1	24	6.9	PRINCE WILLIAM SOUND				
1912	11	7	7	40		7.5	ALASKA: ALASKA PENINSULA				
1915	6	23	4	56		6.2	CALIFORNIA: EL CENTRO	6	1	0.9	1
1915	10	3	6	52	48	7.6	NEVADA: PLEASANT VALLEY				1
1916	2	6	21	51		7.7	ALASKA: ALEUTIAN ISLANDS				
1916	4	18	4	1		7.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
1917	5	31	8	47		7.9	ALASKA: ALASKA PENINSULA				
1918	4	21	22	32		6.8	CALIFORNIA			0.2	1
1922	1	31	13	17		7.6	CALIFORNIA: NORTHERN				1
1923	1	22	9	4	18	7.2	CALIFORNIA: NORTHERN				1
1925	6	28	1	21	5	6.7	MONTANA: CLARKSTON VALLEY			0.15	1
1925	6	29	14	42		6.2	CALIFORNIA: SANTA BARBARA	13	1	8	3
1925	2	23	23	54		6.8	GULF OF ALASKA				
1926	3	20	9	3			HAWAII				
1927	10	24	15	59	44.8	7.1	ALASKA: SE ALASKA				1
1927	1	1	8	16		5.8	CALIFORNIA, MEXICO			1	2
1927	11	4	13	50	43	7.3	CALIFORNIA: S: OFF COAST				2

1929	3	7	1	34		7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
1929	12	17	10	58		7.8	ALASKA: ALEUTIAN ISLANDS: NEAR ISLANDS				
1929	8	12	11	24			NEW YORK: ATTICA				
1930	8	31	0	40	38	5.2	CALIFORNIA: SOUTHERN				1
1932	12	20				7.2	NEVADA: CEDAR MOUNTAIN				
1932	11	10					NEW YORK: WILLETTS POINT				
1933	3	11	1	54	7.8	6.3	CALIFORNIA: LONG BEACH	120	3	40	4
1934	12	31				7.1	CALIFORNIA: BAJA,IMPERIAL VALLEY				
1935	10	31	18	37	47	6	MONTANA: HELENA	2	1	6	3
1935	10	19	4	48	2	6.2	MONTANA: HELENA	2	1	19	3
1935	10	31	18	37	47		ALASKA	15	1	284	
1935	10	19	4	48	2		WASHINGTON: OLYMPIA, SEATTLE, TACOMA	1	1	2000	
1938	11	10	20	18	41.2	8.2	ALASKA				
1940	5	19	4	36	40.9	7.2	CALIFORNIA; MEXICO	9	1	33	4
1940	5	19	4	36	40.9		CALIFORNIA: WHITTIER	8	1	358	
1940	7	14	5	52	53.5	7.4	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				
1941	2	9	9	44	4	6.6	CALIFORNIA: NORTHERN				1
1944	9	5	4	38	45.7	5.6	NEW YORK: MASSENA			2	2
1946	4	1	12	29	1.3	8.6	ALASKA: UNIMAK ISLAND				
1946	11	1	11	14			ALASKA: EAST ALEUTIAN ISLANDS				
1947	4	10	15	58		6.4	CALIFORNIA				2
1948	5	14	22	31		7.5	ALASKA: ALASKA PENINSULA				
1949	11	17	1	19	52		CALIFORNIA: SOUTHERN			9	3
1949	4	13	19	55	42	7	WASHINGTON	8	1	25	4
1949	4	13	19	55	42		CALIFORNIA; MEXICO	9	1	33	
1951	8	21	10	57		6.9	HAWAII				2
1951	8	15	7	23			CALIFORNIA: TERMINAL ISLAND			3	2
1952	8	22	22	41	24	5.8	CALIFORNIA: KERN COUNTY	2	1	10	3
1952	7	21	11	52	14	7.7	CALIFORNIA: KERN COUNTY	12	1	60	4
1952	8	22	22	41	24		CALIFORNIA: PASO ROBLES,TEMPLETON,ATASCADERO	2	1	300	
1952	3	17	3	58			HAWAII				
1954	7	6	11	13		6.8	NEVADA: FALLON				2
1954	8	23				6.8	NEVADA: STILLWATER RANGE				
1954	12	16	11	7		7	NEVADA: DIXIE VALLEY				
1955	1	25	12	23			CALIFORNIA: TERMINAL ISLAND			3	2
1957	3	9	14	22	31.9	8.6	ALASKA				1
1957	3	22	14	21		7.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
1958	7	10	6	15	59.9	7.8	ALASKA: LITUYA BAY				1

1959	8	18	6	37	13.5	7.7	MONTANA: HEBGEN LAKE	28	1	11	3
1959	8	18	6	37	13.5		MONTANA: HELENA	2	1	19	
1961	4	4	21	32			CALIFORNIA: TERMINAL ISLAND			4.5	2
1962	8	30	13	35		5.8	UTAH			2	2
1962	12	21	8	42	43	6.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
1964	3	28	3	36		9.2	ALASKA	15	1	284	4
1964	3	28	3	36			WASHINGTON	8	1	25	
1965	2	4	5	1	21.6	8.7	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				1
1965	7	2	20	58	38.1	6.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				1
1965	4	29	15	28	43.7	6.6	WASHINGTON: SEATTLE	7	1	28	4
1965	4	29	15	28	43.7		WASHINGTON: SEATTLE	7	1	28	
1965	3	30	2	27	3.4	7.6	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				
1969	10	2	4	56	46.5	4.8	CALIFORNIA: SANTA ROSA	1	1	8.35	3
1969	10	2	4	56	46.5		CALIFORNIA: LANDERS, YUCCA VALLEY	3	1	92	
1970	3	11	22	38	34.6	6	ALASKA: ANDREANOF ISLANDS				1
1971	2	9	14	0	41.8		SOUTH CAROLINA: CHARLESTON	60	2	5	
1971	2	9	14	0	41.8	6.5	CALIFORNIA: SAN FERNANDO	65	2	505	4
1971	5	2	6	8	27.3	7.1	ALASKA: ANDREANOF ISLANDS				
1971	11	6	22	0	0.1	5.7	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				
1972	7	30	21	45	14.1	7.6	ALASKA: SITKA, JUNEAU				1
1973	2	21	14	45	57.3	5.7	CALIFORNIA: OXNARD			1	2
1973	4	26	20	26	28.6	6.5	HAWAII: HILO			5.75	3
1975	3	28	2	31	5.7	6	IDAHO: POCATELLO VALLEY			1	2
1975	2	2	8	43	39.1	7.6	ALASKA: ALEUTIAN ISLANDS: NEAR ISLANDS				2
1975	8	1	20	20	12.9	5.6	CALIFORNIA: OROVILLE			3	2
1975	11	29	14	47	40.9	7.7	HAWAII			4	2
1978	8	13	22	54	53.5	5.6	CALIFORNIA: SOUTHERN			15	3
1979	2	28	21	27	8.1	7.5	ALASKA				1
1979	10	15	23	16	54.1	6.9	CALIFORNIA: IMPERIAL VALLEY; MEXICO: MEXICALI			30	4
1980	7	27	18	52	21.8	5.1	KENTUCKY: MAYSVILLE			1	2
1980	5	25	16	33	44.7	6.1	CALIFORNIA: MAMMOTH LAKES			2	2
1980	11	8	10	27	34	7.2	CALIFORNIA: NORTH COAST	5	1	2.75	2
1980	1	24	19	0	9.5	5.9	CALIFORNIA: LIVERMORE			11.5	3
1980	5	18	15	32	11.4	5.2	WASHINGTON: MT ST HELENS				
1981	4	26	12	9	28.4	6	CALIFORNIA: WESTMORLAND,CALIPATRIA			1.5	2
1983	7	12	15	10	3.4	6.1	ALASKA: PRINCE WILLIAM SOUND			1	2
1983	10	28	14	6	6.5		MONTANA: HELENA	2	1	6	
1983	11	16	16	13		6.7	HAWAII: KAPAPALA			6.5	3

1983	10	28	14	6	6.5	7.3	IDAHO: BORAH PEAK, CHALLIS, MACKAY	2	1	12.5	3
1983	5	2	23	42	37.7	6.2	CALIFORNIA: CENTRAL, COALINGA			31	4
1984	10	18	15	30	23	5.1	WYOMING: DOUGLAS, MEDICINE BOW				1
1984	4	24	21	15	19	6.1	CALIFORNIA: CENTRAL: MORGAN HILL			8	3
1986	7	13	13	47	8.2	5.8	CALIFORNIA: SAN DIEGO, NEWPORT BEACH			0.7	1
1986	7	21	14	42	26.6	6.2	CALIFORNIA-NEVADA: CHALFANT VALLEY			1	2
1986	7	8	9	20	44.5	6	CALIFORNIA: PALM SPRINGS			4.5	2
1986	5	7	22	47	10.8	8	ALASKA: ALEUTIAN ISLANDS: ADAK				2
1986	5	17	16	20	22.2	6.4	ALASKA: ANDREANOF ISLANDS				
1987	11	30	19	23	19.5	7.9	ALASKA: YAKUTAT				1
1987	11	24	1	54	14.5	6.2	CALIFORNIA: SUPERSTITION HILLS	2	1	3	2
1987	10	4	10	59	38.1	4.8	CALIFORNIA: WHITTIER, PASADENA	1	1		2
1987	11	24	1	54	14.5		CALIFORNIA: KERN COUNTY	2	1	10	
1987	10	1	14	42	20		MONTANA: HEBGEN LAKE	28	1	11	
1987	10	1	14	42	20	5.7	CALIFORNIA: WHITTIER	8	1	358	4
1987	11	17	8	46	53.3	7.2	GULF OF ALASKA				
1988	3	6	22	35	36.9	7.8	ALASKA: GULF OF ALASKA: ANCHORAGE				1
1989	6	26	3	27	3.9	6.1	HAWAIIAN ISLANDS: PUNA DISTRICT				2
1989	10	18	0	4	15.2		CALIFORNIA: ARCADIA, GLENDALE, LOS ANGELES	2	1	33.5	
1989	10	18	0	4	15.2	6.9	CALIFORNIA: LOMA PRIETA	62	2	5600	4
1989	9	4	13	14	58.2	6.9	ALASKA				
1990	2	28	23	43	36.6	5.5	CALIFORNIA: S, CLAREMONT, COVINA			12.7	3
1991	8	17	19	29	40	6.2	CALIFORNIA: HONEYDEW, WHITETHORN, PETROLIA				2
1991	6	28	14	43	54.5		CALIFORNIA: SANTA ROSA	1	1	8.35	
1991	6	28	14	43	54.5	5.1	CALIFORNIA: ARCADIA, GLENDALE, LOS ANGELES	2	1	33.5	4
1992	4	23	4	50	23.2	6.3	CALIFORNIA: JOSHUA TREE, ANGELUS OAKS				2
1992	6	28	15	5	30.7	6.7	CALIFORNIA: BIG BEAR LAKE, BIG BEAR CITY				2
1992	6	29	10	14	22.2	5.4	NEVADA-CALIFORNIA BORDER: NEVADA TEST SITE				2
1992	6	28	11	57	34.1		IDAHO: BORAH PEAK, CHALLIS, MACKAY	2	1	12.5	
1992	4	25	18	6	4.2	7.1	CALIFORNIA: HUMBOLDT COUNTY: FERNDALE, PETROLIA			75	4
1992	6	28	11	57	34.1	7.6	CALIFORNIA: LANDERS, YUCCA VALLEY	3	1	92	4
1993	9	21	3	28	55.4	6	OREGON: KLAMATH FALLS	2	1	7.5	3
1993	3	25	13	34	35.4	5.6	WASHINGTON-OREGON BORDER			28.4	4
1994	1	17	12	30	55.3		CALIFORNIA: HAYWARD,SAN FRANCISCO	30	1	0.35	
1994	1	16	1	49	16.2	4.6	PENNSYLVANIA: READING, FELT TO CANADA				1
1994	2	3	9	5	4.2	5.8	WYOMING: AFTON				1
1994	9	1	15	15	53	7	CALIFORNIA: NORTH: HONEYDEW				1

1994	12	26	14	10	29.1	5.5	CALIFORNIA: EUREKA, SAMOA, ARCATA, BLUE LAKE			2.1	2
1994	1	17	12	30	55.3	6.7	CALIFORNIA: NORTHRIDGE	60	2	40000	4
1995	10	6	5	23	18.5	6	ALASKA: FAIRBANKS NORTH STAR COUNTY				1
1996	6	10	4	3	35.4	7.9	ALASKA: ANDREANOF ISLANDS				
1996	6	10	15	24	56	7.3	ALASKA: ANDREANOF ISLANDS				
1999	10	16	9	46	44.1	7.2	CALIFORNIA: LUDLOW, LANDERS, TWENTYNINE PALMS				1
2000	9	3	8	36	30	5	CALIFORNIA: NAPA			50	4
2001	9	9	23	59	18	4.2	CALIFORNIA: LOS ANGELES				1
2001	2	28	18	54	32.8		CALIFORNIA: SUPERSTITION HILLS	2	1	3	
2001	2	28	18	54	32.8	6.8	WASHINGTON: OLYMPIA, SEATTLE, TACOMA	1	1	2000	4
2002	4	20	10	50	47.5	5.2	NEW YORK: CLINTON, ESSEX, AU SABLE FORKS				1
2002	10	23	11	27	19.4	6.7	ALASKA: CANTWELL, DENALI NATL PARK				2
2002	11	3	22	12	41	7.9	ALASKA: SLANA, MENTASTA LAKE, FAIRBANKS			56	4
2003	12	22	19	15	56		CALIFORNIA: OWENS VALLEY	27	1	0.25	
2003	2	22	12	19	10.5	5.2	CALIFORNIA: BIG BEAR CITY				1
2003	6	6	12	29	34	4	KENTUCKY: BARDWELL				1
2003	4	29	8	59	39	4.6	ALABAMA: FORT PAYNE,GAYLESVILLE,VALLEY HEAD				1
2003	12	22	19	15	56	6.6	CALIFORNIA: PASO ROBLES,TEMPLETON,ATASCADERO	2	1	300	4
2003	11	17	6	43	6.8	7.8	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS				
2004	9	28	17	15	24.2	6	CALIFORNIA: CENTRAL: PARKFIELD, SAN MIGUEL				1
2005	7	26	4	8	37.1	5.6	MONTANA: DILLON, SILVER STAR, TWIN BRIDGES				1
2005	6	15	2	50	53.1	7.2	CALIFORNIA: OFF COAST NORTHERN				
2006	10	15	17	7	49.2	6.7	HAWAIIAN ISLANDS			73	4
2007	5	8	15	46	49.1	4.5	MONTANA: SHERIDAN				1
2007	7	20	11	42	22.3	4.2	CALIFORNIA: MONTCLAIR				1
2007	10	31	3	4	54.8	5.6	CALIFORNIA: SAN JOSE				1
2007	8	2	3	21	42.8	6.7	ALASKA: ALEUTIAN ISLANDS				
2007	8	6	8	48	40	4.2	UTAH: HUNTINGTON	9	1		
2007	8	17	0	38	56	1.6	UTAH	3	1		
2008	4	18	9	36	59.1	5.3	ILLINOIS: WEST SALEM				1
2008	4	26	6	40	10.6	5	NEVADA: FALLON				1
2008	7	29	18	42	15.7	5.4	CALIFORNIA: LOS ANGELES				1
2008	2	21	14	16	2.7	6	NEVADA: WELLS				2
2010	6	15	4	26	58.4	5.8	CALIFORNIA: OCOTILLO				1
2010	12	19	5	5	30	3.7	OKLAHOMA: LUTHER				1
2010	1	10	0	27	39.3	6.5	CALIFORNIA: OFF COAST NORTHERN			21.8	3
2011	2	17	22	47	21.5	3.1	COLORADO: PAONIA				1
2011	11	8	2	46	57	5	OKLAHOMA: SPARKS, PRAGUE				1

2011	11	6	3	53	10	5.7	OKLAHOMA: SPARKS				2
2011	8	23	17	51	4.5	5.8	VIRGINIA: LOUISA COUNTY, MARYLAND, WASHINGTON D.C.				2
2011	8	23	5	46	18.2	5.4	COLORADO: SEGUNDO				2
2011	6	24	3	9	39.4	7.3	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
2011	9	2	10	55	53.5	6.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS				
2013	4	18	0	50	38.5	2.1	TEXAS: WEST	14	1	100	4
2013	1	5	8	58	19.3	7.5	ALASKA: SOUTHEASTERN				
2014	3	29	4	9	42	5.1	CALIFORNIA: LA HABRA, BREA, FULLERTON			10.8	3
2014	8	24	10	20	44	6	CALIFORNIA: NAPA, VALLEJO	1	1	362	4
2014	6	23	20	53	10	7.9	ALASKA: ALEUTIAN ISLANDS				
2014	7	25	10	54	49	6.1	ALASKA				

Table C.4: Earthquake data by individual events with description values from Table C.3 (page 98) included in the values of fatalities (Total Deaths) and economic loss (Total Damage). Output data provides important information including: year, month, day, hour, minute, second, magnitude, name, number of deaths, and economic loss in millions (at time of event).

YEAR	MO	DY	HR	MIN	SEC	MAG	LOCATION_NAME	TOT_DTH	TOT_DAM
1900	10	9	12	25		8.3	ALASKA: KODIAK ISLAND		905000
1900	8	11	4	40			SE. ALASKA	25	
1901	12	31	9	2	30	7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		500000
1901	3	3	7	45		6.4	CALIFORNIA: SAN DIEGO		905000
1902	4	29	6	57			CALIFORNIA: SOUTHERN		2500000
1902	1	1	5	20		7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
1903	6	2	13	17		8.3	ALASKA: SOUTHWEST		
1904	8	27	21	56		8.3	ALASKA: RAMPART		
1905	2	14	8	46		7.9	ALASKA: ANDREANOF ISLANDS		
1906	4	18	13	12	21	7.9	CALIFORNIA: SAN FRANCISCO	700	400000000
1906	8	17	0	10	42	7.8	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		
1906	12	23	17	22		7.6	ALASKA: ALEUTIAN ISLANDS		
1907	9	2	16	1		7.8	ALASKA: ALEUTIAN ISLANDS		
1907	9	24	12	59		5.5	ALASKA: SKAGWAY		
1908	2	14	11	25		6	ALASKA GULF		
1908	9	21	6	31		6.8	HAWAII		
1909	4	10	19	36		7.8	ALASKA: ALEUTIAN ISLANDS		
1911	9	22	5	1	24	6.9	PRINCE WILLIAM SOUND		905000
1912	11	7	7	40		7.5	ALASKA: ALASKA PENINSULA		
1915	6	23	4	56		6.2	CALIFORNIA: EL CENTRO	6	900000
1915	10	3	6	52	48	7.6	NEVADA: PLEASANT VALLEY		905000
1916	2	6	21	51		7.7	ALASKA: ALEUTIAN ISLANDS		
1916	4	18	4	1		7.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
1917	5	31	8	47		7.9	ALASKA: ALASKA PENINSULA		
1918	4	21	22	32		6.8	CALIFORNIA		200000
1922	1	31	13	17		7.6	CALIFORNIA: NORTHERN		500000
1923	1	22	9	4	18	7.2	CALIFORNIA: NORTHERN		905000
1925	6	28	1	21	5	6.7	MONTANA: CLARKSTON VALLEY		150000
1925	6	29	14	42		6.2	CALIFORNIA: SANTA BARBARA	13	8000000
1925	2	23	23	54		6.8	GULF OF ALASKA		
1926	3	20	9	3			HAWAII		
1927	10	24	15	59	44.8	7.1	ALASKA: SE ALASKA		500000
1927	1	1	8	16		5.8	CALIFORNIA, MEXICO	25	3000000
1927	11	4	13	50	43	7.3	CALIFORNIA: S: OFF COAST		4525000

1929	3	7	1	34		7.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
1929	12	17	10	58		7.8	ALASKA: ALEUTIAN ISLANDS: NEAR ISLANDS		
1929	8	12	11	24			NEW YORK: ATTICA		
1930	8	31	0	40	38	5.2	CALIFORNIA: SOUTHERN	25	905000
1932	12	20				7.2	NEVADA: CEDAR MOUNTAIN		
1932	11	10					NEW YORK: WILLETTS POINT		
1933	3	11	1	54	7.8	6.3	CALIFORNIA: LONG BEACH	120	40000000
1934	12	31				7.1	CALIFORNIA: BAJA,IMPERIAL VALLEY		
1935	10	31	18	37	47	6	MONTANA: HELENA	2	6000000
1935	10	19	4	48	2	6.2	MONTANA: HELENA	2	19000000
1935	10	31	18	37	47		ALASKA	15	284000000
1935	10	19	4	48	2		WASHINGTON: OLYMPIA, SEATTLE, TACOMA	1	2000000000
1938	11	10	20	18	41.2	8.2	ALASKA		
1940	5	19	4	36	40.9	7.2	CALIFORNIA; MEXICO	9	33000000
1940	5	19	4	36	40.9		CALIFORNIA: WHITTIER	8	358000000
1940	7	14	5	52	53.5	7.4	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		
1941	2	9	9	44	4	6.6	CALIFORNIA: NORTHERN		905000
1944	9	5	4	38	45.7	5.6	NEW YORK: MASSENA		2000000
1946	4	1	12	29	1.3	8.6	ALASKA: UNIMAK ISLAND	500	26046000
1946	11	1	11	14			ALASKA: EAST ALEUTIAN ISLANDS		
1947	4	10	15	58		6.4	CALIFORNIA		2500000
1948	5	14	22	31		7.5	ALASKA: ALASKA PENINSULA		
1949	11	17	1	19	52		CALIFORNIA: SOUTHERN		9000000
1949	4	13	19	55	42	7	WASHINGTON	8	25000000
1949	4	13	19	55	42		CALIFORNIA; MEXICO	9	33000000
1951	8	21	10	57		6.9	HAWAII		2500000
1951	8	15	7	23			CALIFORNIA: TERMINAL ISLAND		3000000
1952	8	22	22	41	24	5.8	CALIFORNIA: KERN COUNTY	2	10000000
1952	7	21	11	52	14	7.7	CALIFORNIA: KERN COUNTY	12	60000000
1952	8	22	22	41	24		CALIFORNIA: PASO ROBLES,TEMPLETON,ATASCADERO	2	300000000
1952	3	17	3	58			HAWAII		
1954	7	6	11	13		6.8	NEVADA: FALLON		2500000
1954	8	23				6.8	NEVADA: STILLWATER RANGE		
1954	12	16	11	7		7	NEVADA: DIXIE VALLEY		
1955	1	25	12	23			CALIFORNIA: TERMINAL ISLAND		3000000
1957	3	9	14	22	31.9	8.6	ALASKA	25	22625000
1957	3	22	14	21		7.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
1958	7	10	6	15	59.9	7.8	ALASKA: LITUYA BAY	25	100000
1959	8	18	6	37	13.5	7.7	MONTANA: HEBGEN LAKE	28	11000000

1959	8	18	6	37	13.5		MONTANA: HELENA	2	19000000
1961	4	4	21	32			CALIFORNIA: TERMINAL ISLAND		4500000
1962	8	30	13	35		5.8	UTAH		2000000
1962	12	21	8	42	43	6.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
1964	3	28	3	36		9.2	ALASKA	15	400000000
1964	3	28	3	36			WASHINGTON	8	
1965	2	4	5	1	21.6	8.7	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		10000
1965	7	2	20	58	38.1	6.5	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		905000
1965	4	29	15	28	43.7	6.6	WASHINGTON: SEATTLE	7	28000000
1965	4	29	15	28	43.7		WASHINGTON: SEATTLE	7	28000000
1965	3	30	2	27	3.4	7.6	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		
1969	10	2	4	56	46.5	4.8	CALIFORNIA: SANTA ROSA	1	8350000
1969	10	2	4	56	46.5		CALIFORNIA: LANDERS, YUCCA VALLEY	3	92000000
1970	3	11	22	38	34.6	6	ALASKA: ANDREANOF ISLANDS		905000
1971	2	9	14	0	41.8		SOUTH CAROLINA: CHARLESTON	60	5000000
1971	2	9	14	0	41.8	6.5	CALIFORNIA: SAN FERNANDO	65	505000000
1971	5	2	6	8	27.3	7.1	ALASKA: ANDREANOF ISLANDS		
1971	11	6	22	0	0.1	5.7	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		
1972	7	30	21	45	14.1	7.6	ALASKA: SITKA, JUNEAU		905000
1973	2	21	14	45	57.3	5.7	CALIFORNIA: OXNARD		1000000
1973	4	26	20	26	28.6	6.5	HAWAII: HILO		5750000
1975	3	28	2	31	5.7	6	IDAHO: POCATELLO VALLEY		1000000
1975	2	2	8	43	39.1	7.6	ALASKA: ALEUTIAN ISLANDS: NEAR ISLANDS		2500000
1975	8	1	20	20	12.9	5.6	CALIFORNIA: OROVILLE		3000000
1975	11	29	14	47	40.9	7.7	HAWAII	25	4000000
1978	8	13	22	54	53.5	5.6	CALIFORNIA: SOUTHERN		15000000
1979	2	28	21	27	8.1	7.5	ALASKA		905000
1979	10	15	23	16	54.1	6.9	CALIFORNIA: IMPERIAL VALLEY; MEXICO: MEXICALI		30000000
1980	7	27	18	52	21.8	5.1	KENTUCKY: MAYSVILLE		1000000
1980	5	25	16	33	44.7	6.1	CALIFORNIA: MAMMOTH LAKES		2000000
1980	11	8	10	27	34	7.2	CALIFORNIA: NORTH COAST	5	2750000
1980	1	24	19	0	9.5	5.9	CALIFORNIA: LIVERMORE		11500000
1980	5	18	15	32	11.4	5.2	WASHINGTON: MT ST HELENS	75	2000000000
1981	4	26	12	9	28.4	6	CALIFORNIA: WESTMORLAND,CALIPATRIA		1500000
1983	7	12	15	10	3.4	6.1	ALASKA: PRINCE WILLIAM SOUND		1000000
1983	10	28	14	6	6.5		MONTANA: HELENA	2	6000000
1983	11	16	16	13		6.7	HAWAII: KAPAPALA		6500000
1983	10	28	14	6	6.5	7.3	IDAHO: BORAH PEAK, CHALLIS, MACKAY	2	22625000
1983	5	2	23	42	37.7	6.2	CALIFORNIA: CENTRAL, COALINGA		31000000

1984	10	18	15	30	23	5.1	WYOMING: DOUGLAS, MEDICINE BOW		905000
1984	4	24	21	15	19	6.1	CALIFORNIA: CENTRAL: MORGAN HILL		8000000
1986	7	13	13	47	8.2	5.8	CALIFORNIA: SAN DIEGO, NEWPORT BEACH		700000
1986	7	21	14	42	26.6	6.2	CALIFORNIA-NEVADA: CHALFANT VALLEY		1000000
1986	7	8	9	20	44.5	6	CALIFORNIA: PALM SPRINGS		4500000
1986	5	7	22	47	10.8	8	ALASKA: ALEUTIAN ISLANDS: ADAK		4525000
1986	5	17	16	20	22.2	6.4	ALASKA: ANDREANOF ISLANDS		
1987	11	30	19	23	19.5	7.9	ALASKA: YAKUTAT		905000
1987	11	24	1	54	14.5	6.2	CALIFORNIA: SUPERSTITION HILLS	2	3000000
1987	10	4	10	59	38.1	4.8	CALIFORNIA: WHITTIER, PASADENA	1	4525000
1987	11	24	1	54	14.5		CALIFORNIA: KERN COUNTY	2	10000000
1987	10	1	14	42	20		MONTANA: HEBGEN LAKE	28	11000000
1987	10	1	14	42	20	5.7	CALIFORNIA: WHITTIER	8	358000000
1987	11	17	8	46	53.3	7.2	GULF OF ALASKA		
1988	3	6	22	35	36.9	7.8	ALASKA: GULF OF ALASKA: ANCHORAGE		905000
1989	6	26	3	27	3.9	6.1	HAWAIIAN ISLANDS: PUNA DISTRICT		4525000
1989	10	18	0	4	15.2		CALIFORNIA: ARCADIA, GLENDALE, LOS ANGELES	2	33500000
1989	10	18	0	4	15.2	6.9	CALIFORNIA: LOMA PRIETA	62	5600000000
1989	9	4	13	14	58.2	6.9	ALASKA		
1990	2	28	23	43	36.6	5.5	CALIFORNIA: S, CLAREMONT, COVINA		12700000
1991	8	17	19	29	40	6.2	CALIFORNIA: HONEYDEW, WHITETHORN, PETROLIA		4525000
1991	6	28	14	43	54.5		CALIFORNIA: SANTA ROSA	1	8350000
1991	6	28	14	43	54.5	5.1	CALIFORNIA: ARCADIA, GLENDALE, LOS ANGELES	2	33500000
1992	4	23	4	50	23.2	6.3	CALIFORNIA: JOSHUA TREE, ANGELUS OAKS		4525000
1992	6	28	15	5	30.7	6.7	CALIFORNIA: BIG BEAR LAKE, BIG BEAR CITY		4525000
1992	6	29	10	14	22.2	5.4	NEVADA-CALIFORNIA BORDER: NEVADA TEST SITE		4525000
1992	6	28	11	57	34.1		IDAHO: BORAH PEAK, CHALLIS, MACKAY	2	12500000
1992	4	25	18	6	4.2	7.1	CALIFORNIA: HUMBOLDT COUNTY: FERNDALE, PETROLIA		75000000
1992	6	28	11	57	34.1	7.6	CALIFORNIA: LANDERS, YUCCA VALLEY	3	92000000
1993	9	21	3	28	55.4	6	OREGON: KLAMATH FALLS	2	7500000
1993	3	25	13	34	35.4	5.6	WASHINGTON-OREGON BORDER		28400000
1994	1	17	12	30	55.3		CALIFORNIA: HAYWARD,SAN FRANCISCO	30	350000
1994	1	16	1	49	16.2	4.6	PENNSYLVANIA: READING, FELT TO CANADA		905000
1994	2	3	9	5	4.2	5.8	WYOMING: AFTON		905000
1994	9	1	15	15	53	7	CALIFORNIA: NORTH: HONEYDEW		905000
1994	12	26	14	10	29.1	5.5	CALIFORNIA: EUREKA, SAMOA, ARCATA, BLUE LAKE		2100000
1994	1	17	12	30	55.3	6.7	CALIFORNIA: NORTHRIDGE	60	40000000000
1995	10	6	5	23	18.5	6	ALASKA: FAIRBANKS NORTH STAR COUNTY		905000
1996	6	10	4	3	35.4	7.9	ALASKA: ANDREANOF ISLANDS		

1996	6	10	15	24	56	7.3	ALASKA: ANDREANOF ISLANDS		
1999	10	16	9	46	44.1	7.2	CALIFORNIA: LUDLOW, LANDERS, TWENTYNINE PALMS		905000
2000	9	3	8	36	30	5	CALIFORNIA: NAPA		50000000
2001	9	9	23	59	18	4.2	CALIFORNIA: LOS ANGELES		905000
2001	2	28	18	54	32.8		CALIFORNIA: SUPERSTITION HILLS	2	3000000
2001	2	28	18	54	32.8	6.8	WASHINGTON: OLYMPIA, SEATTLE, TACOMA	1	2000000000
2002	4	20	10	50	47.5	5.2	NEW YORK: CLINTON, ESSEX, AU SABLE FORKS		905000
2002	10	23	11	27	19.4	6.7	ALASKA: CANTWELL, DENALI NATL PARK		4525000
2002	11	3	22	12	41	7.9	ALASKA: SLANA, MENTASTA LAKE, FAIRBANKS		56000000
2003	12	22	19	15	56		CALIFORNIA: OWENS VALLEY	27	250000
2003	2	22	12	19	10.5	5.2	CALIFORNIA: BIG BEAR CITY		905000
2003	6	6	12	29	34	4	KENTUCKY: BARDWELL		905000
2003	4	29	8	59	39	4.6	ALABAMA: FORT PAYNE,GAYLESVILLE,VALLEY HEAD		905000
2003	12	22	19	15	56	6.6	CALIFORNIA: PASO ROBLES,TEMPLETON,ATASCADERO	2	300000000
2003	11	17	6	43	6.8	7.8	ALASKA: ALEUTIAN ISLANDS: RAT ISLANDS		
2004	9	28	17	15	24.2	6	CALIFORNIA: CENTRAL: PARKFIELD, SAN MIGUEL		905000
2005	7	26	4	8	37.1	5.6	MONTANA: DILLON, SILVER STAR, TWIN BRIDGES		905000
2005	6	15	2	50	53.1	7.2	CALIFORNIA: OFF COAST NORTHERN		
2006	10	15	17	7	49.2	6.7	HAWAIIAN ISLANDS		73000000
2007	5	8	15	46	49.1	4.5	MONTANA: SHERIDAN		905000
2007	7	20	11	42	22.3	4.2	CALIFORNIA: MONTCLAIR		905000
2007	10	31	3	4	54.8	5.6	CALIFORNIA: SAN JOSE		905000
2007	8	2	3	21	42.8	6.7	ALASKA: ALEUTIAN ISLANDS		
2007	8	6	8	48	40	4.2	UTAH: HUNTINGTON	9	
2007	8	17	0	38	56	1.6	UTAH	3	
2008	4	18	9	36	59.1	5.3	ILLINOIS: WEST SALEM		905000
2008	4	26	6	40	10.6	5	NEVADA: FALLON		905000
2008	7	29	18	42	15.7	5.4	CALIFORNIA: LOS ANGELES		905000
2008	2	21	14	16	2.7	6	NEVADA: WELLS		4525000
2010	6	15	4	26	58.4	5.8	CALIFORNIA: OCOTILLO		905000
2010	12	19	5	5	30	3.7	OKLAHOMA: LUTHER		905000
2010	1	10	0	27	39.3	6.5	CALIFORNIA: OFF COAST NORTHERN		21800000
2011	2	17	22	47	21.5	3.1	COLORADO: PAONIA		905000
2011	11	8	2	46	57	5	OKLAHOMA: SPARKS, PRAGUE		905000
2011	11	6	3	53	10	5.7	OKLAHOMA: SPARKS		4525000
2011	8	23	17	51	4.5	5.8	VIRGINIA: LOUISA COUNTY, MARYLAND, WASHINGTON D.C.		4525000
2011	8	23	5	46	18.2	5.4	COLORADO: SEGUNDO		4525000
2011	6	24	3	9	39.4	7.3	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		
2011	9	2	10	55	53.5	6.8	ALASKA: ALEUTIAN ISLANDS: FOX ISLANDS		

2013	4	18	0	50	38.5	2.1	TEXAS: WEST	14	100000000
2013	1	5	8	58	19.3	7.5	ALASKA: SOUTHEASTERN		
2014	3	29	4	9	42	5.1	CALIFORNIA: LA HABRA, BREA, FULLERTON		10800000
2014	8	24	10	20	44	6	CALIFORNIA: NAPA, VALLEJO	1	362000000
2014	6	23	20	53	10	7.9	ALASKA: ALEUTIAN ISLANDS		
2014	7	25	10	54	49	6.1	ALASKA		

APPENDIX D

National Weather Service Storm Damage Survey

Highly publicized damaging and historic tornado outbreaks in April and June of this year (2011) have led to a substantial increase in public interest in National Weather Service storm surveys. When tornadoes occur, National Weather Service meteorologists are assigned the task of completing a thorough damage survey. A survey team's mission is to gather data in order to reconstruct a tornado's life cycle, including where it occurred, when and where it initially touched down and lifted (path length), its width, and its size. It should also be mentioned that survey teams are occasionally tasked with determining whether damage may have been caused by straight line winds or a tornado and assessing the size of straight line winds. With respect to tornado damage surveys, one of the most difficult tasks is assigning a rating to a tornado.

Before February 2007, tornado strength was rated based on the Fujita Scale. However, there were some flaws with the original Fujita Scale. For instance, it did not account for the quality of building construction. Beginning in 2001, it was determined that the Fujita Scale needed to be modified, and a committee of meteorologists, engineers, and academia was formed to begin developing a new scale. In February 2007, the new Enhanced Fujita Scale (Table D.1) became operational and is still the scale used to rate the size of tornadoes.

EF Number	*3-Second Wind Gust (mph)*
0	65 - 85
1	86 - 110
2	111 - 135
3	136 - 165
4	166 - 200
5	Over 200

Table D.1. Enhanced Fujita Scale for rating tornado size.

Before a survey team is deployed, they will be equipped with a variety of technology to complete the survey. Typically, a damage survey kit will contain a GPS unit, a cell phone, a laptop with damage survey software, a digital camera, an atlas or gazetteer, and a notebook (Image D.1). After a survey team is assigned and the survey kit is prepared, the team then drives to the reported tornado damage location(s). Most commonly, a survey team will conduct a full ground survey in order to assess tornado damage, but occasionally, a team may also conduct an aerial survey if the spatial extent of the damage is large enough.

Figure D.1. Damage survey kit includes maps, camera, and a GPS.

Depending on the survey team, the starting and ending point of the tornado may be determined first followed by the width of the tornado. The time of the tornado's life cycle may be confirmed through eyewitness accounts and/or radar data. To determine the size of the tornado, the survey team will attempt to find the worst damage since this is how the tornado will ultimately be rated. Once the worst damage is identified, the survey team will assign a damage indicator to the structure or object. There are 28 damage indicators, including one- or two-family residences, manufactured homes, motels, warehouses, schools, small retail buildings (e.g. fast food restaurants), and even trees. Each one of the damage indicators has a description of the typical construction for that category of indicator. For example, typical construction for one- and two-family residences includes asphalt shingles, tile, slate or metal roofing, attached single car garage, and brick veneer, wood panels, stucco, vinyl or metal siding.

Once the structure or object has been assigned a damage indicator, the team will begin a thorough analysis of the building structure and construction. The survey team will then assign a degree of damage to the structure or object. The degree of damage has several different categories, and each category has an expected wind speed and a lower and upper bound wind speed. For one- and two-family residences, if a tornado breaks glass in windows and doors, the expected wind speed is 96 mph, the lower bound wind speed is 79 mph, and the upper bound wind speed is 114 mph. If a tornado produces damage that results in the collapse of all interior and exterior walls, the expected wind speed is 170 mph, the lower bound wind speed is 142 mph, and the upper bound wind speed is 198 mph. This is where the job becomes difficult for the survey team because the team must know some basics about construction. If the quality of construction meets strict building code, the survey team will likely assign an expected wind speed to the damage. If the construction fails to meet code, a lower bound wind speed may be assigned, but if the construction exceeds code and/or is well-engineered, it may be assigned an upper bound wind speed. Once the expected, lower bound, or upper bound wind speed is determined, it is applied to the EF Scale to assign a rating.

Let's look at an example to help tie everything together. For an interactive demonstration, this link will be very helpful: http://www.spc.noaa.gov/efscale/ef-scale.html. A tornado strikes a house, causing the entire roof to be blown off, but all the walls remain standing. The survey team will first assign a damage indicator of 2 since this is a one- or two-family residence. The description of the damage corresponds best to a degree of damage of 6 (http://www.spc.noaa.gov/efscale/2.html). After careful inspection of the construction quality, it is observed that the ceiling joust was fastened with rafter clips to exterior walls, which meets code. Therefore, the survey team assigns an expected wind speed of 122 mph. Based on this wind speed, the team assigns the tornado a rating of EF-2 with winds between 111-135 mph.

For more information about the EF Scale, please visit http://www.spc.noaa.gov/efscale

APPENDIX E

PLOTS OF DRIFT IN DATA OVER TIME

Data divided into two time intervals and plotted on same plots as Figures 3.1-3.8 (pages 26-35).

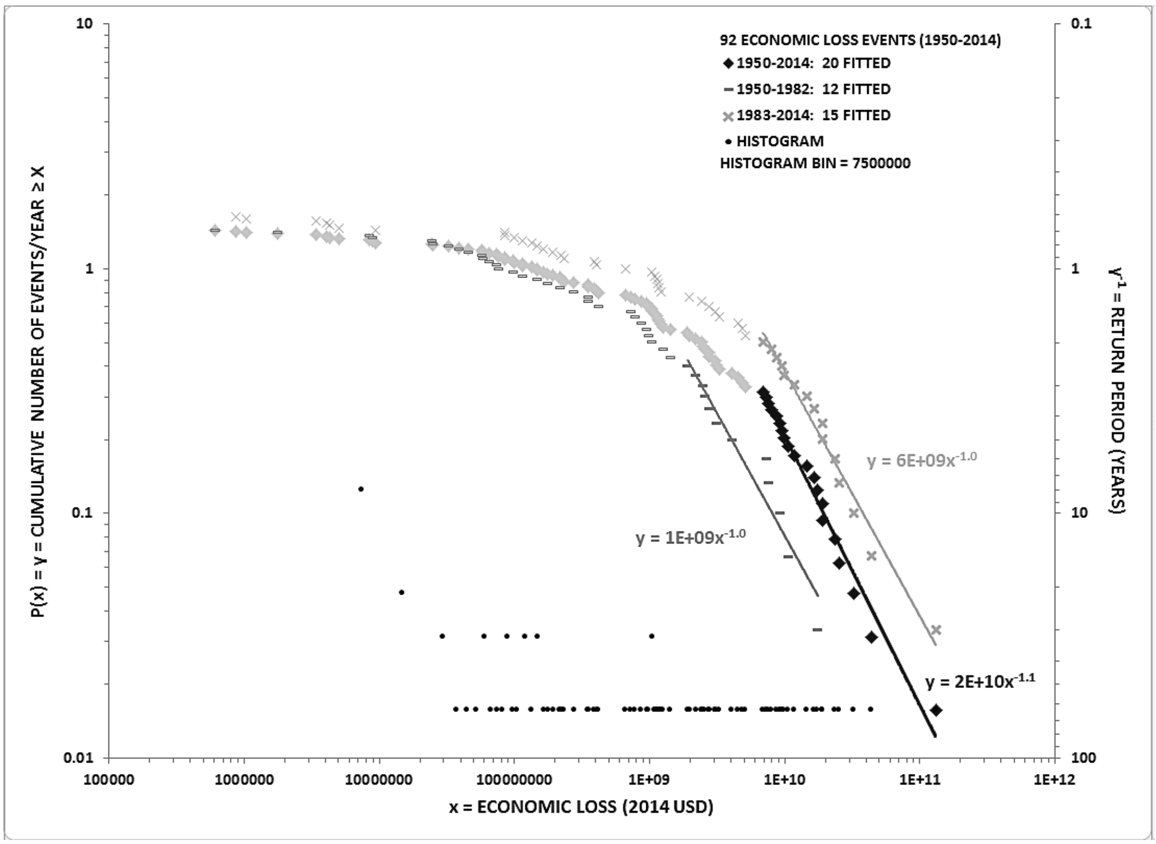


Figure E.1: Size-cumulative frequency plot of hurricane economic losses for 92 of 94 individual events in the United States, 1950-2014. Data greater than $7 billion are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1950-1982 and 1983-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is $7.5 million.

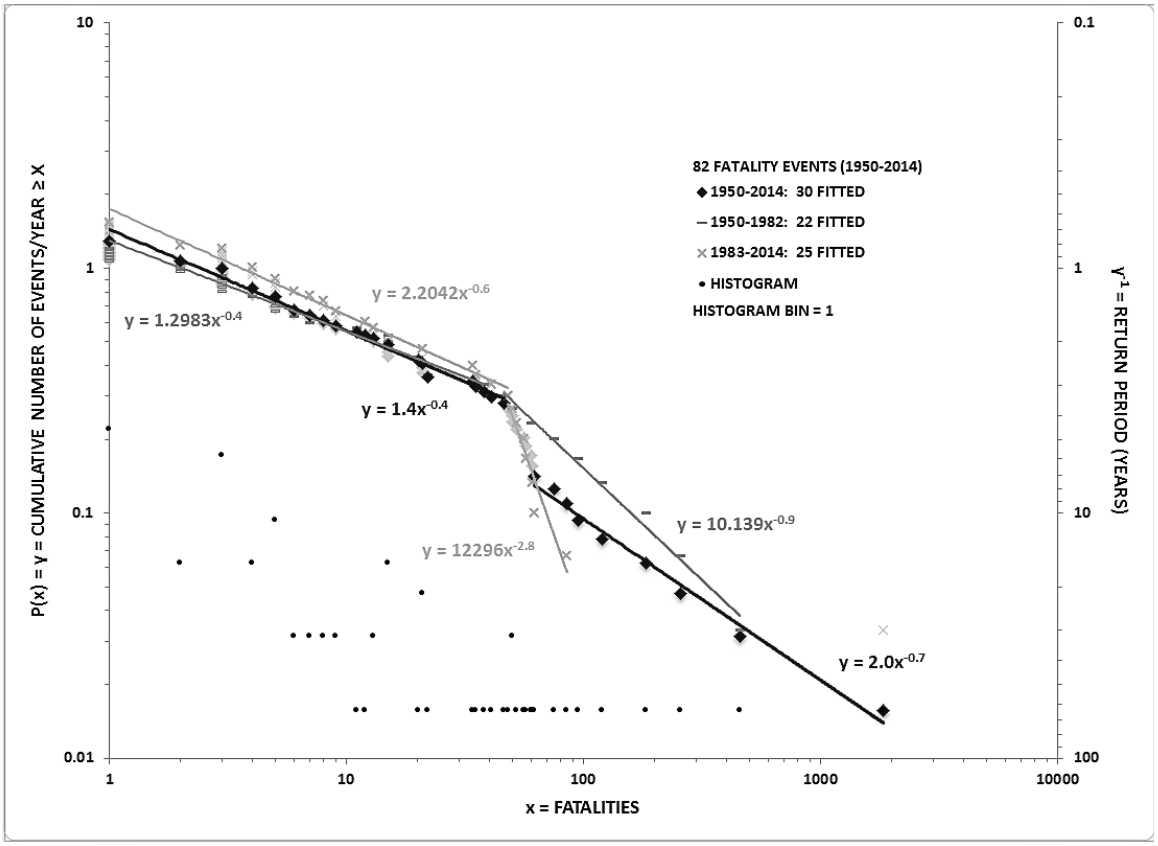


Figure E.2. Size-cumulative frequency plot of hurricane fatalities for 82 of 94 individual events in the United States, 1950-2014. Data greater than 60 fatalities and the data below 50 fatalities are well fit by separate power functions. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1950-1982 and 1983-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

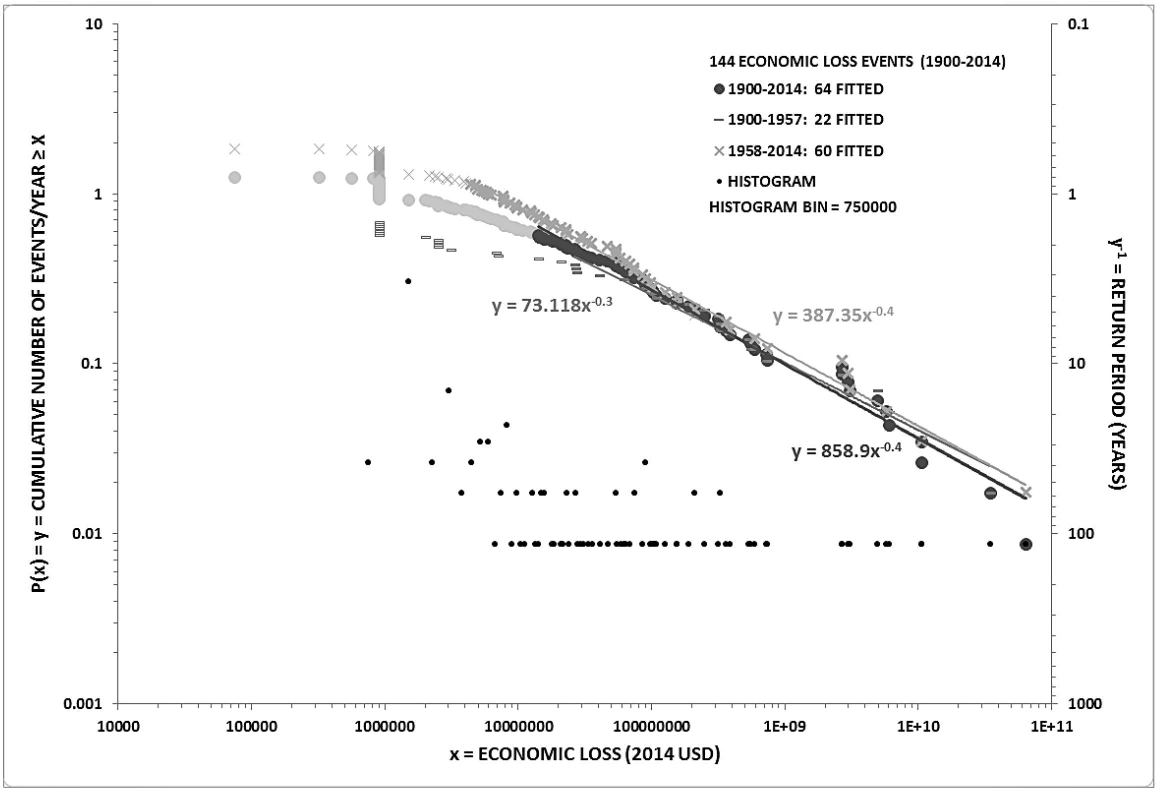


Figure E.3. Size-cumulative frequency plot of earthquake economic losses for 144 of 196 individual events in the United States, 1900-2014. Data greater than $20 million are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1900-1957 and 1958-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is $750,000.

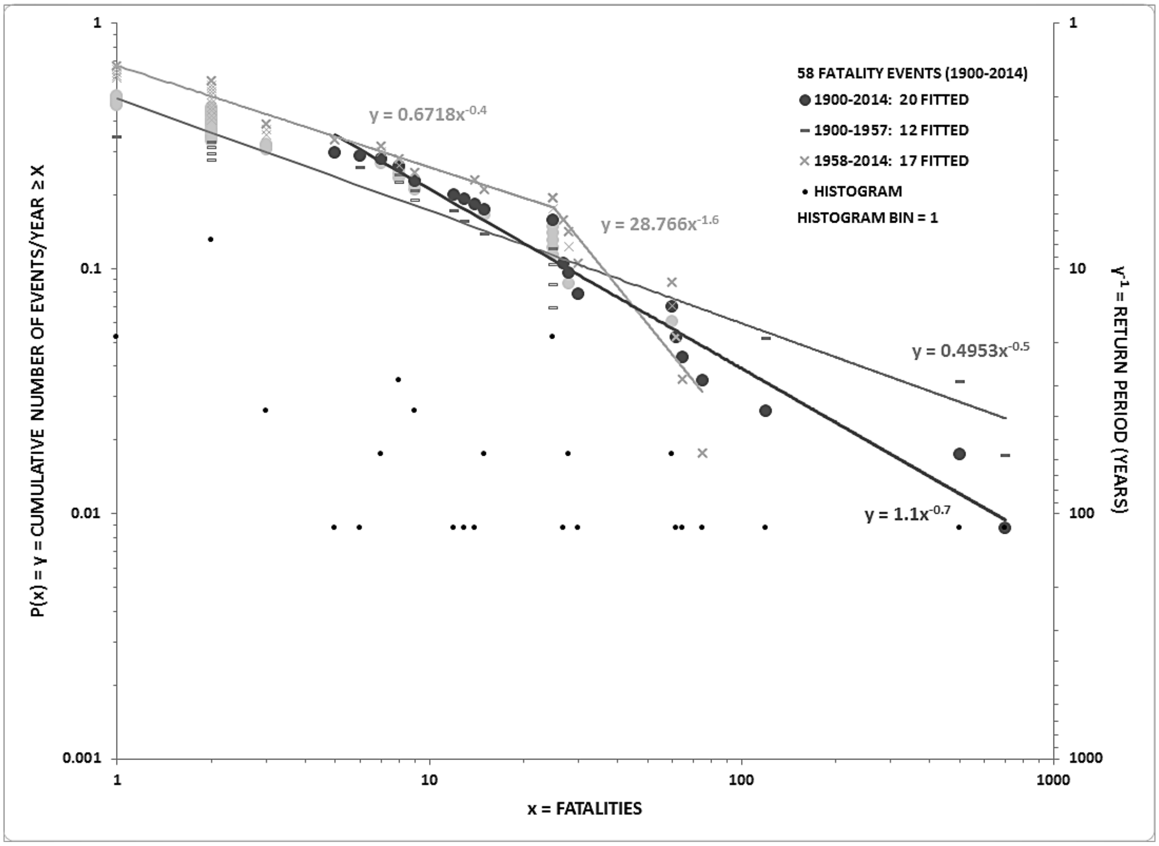


Figure E.4. Size-cumulative frequency plot of earthquake fatalities for 58 of 196 individual events in the United States, 1900-2014. Data greater than 5 fatalities are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1900-1957 and 1958-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

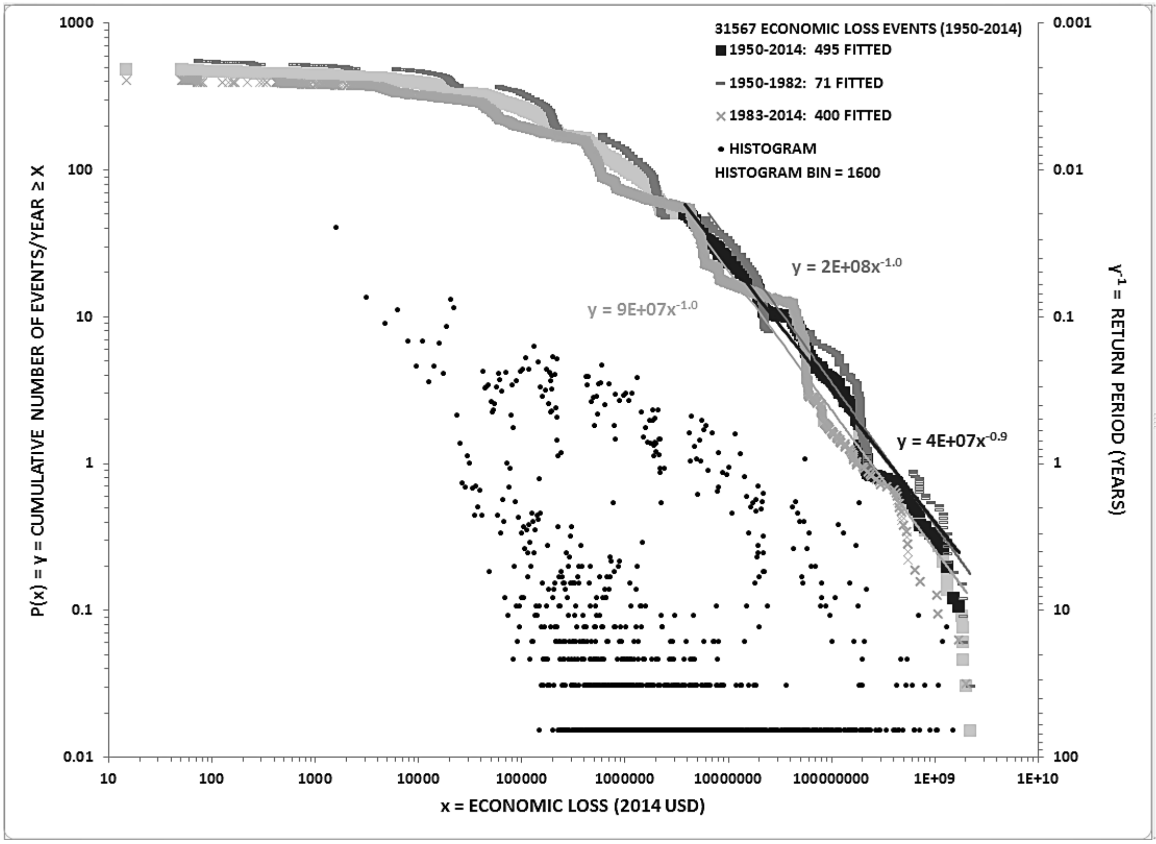


Figure E.5. Size-cumulative frequency plot of tornado economic losses for 31,567 of 46,402 individual events in the United States, 1900-2014. Data between $4 million and $2 billion are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1950-1982 and 1983-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is $1,600.

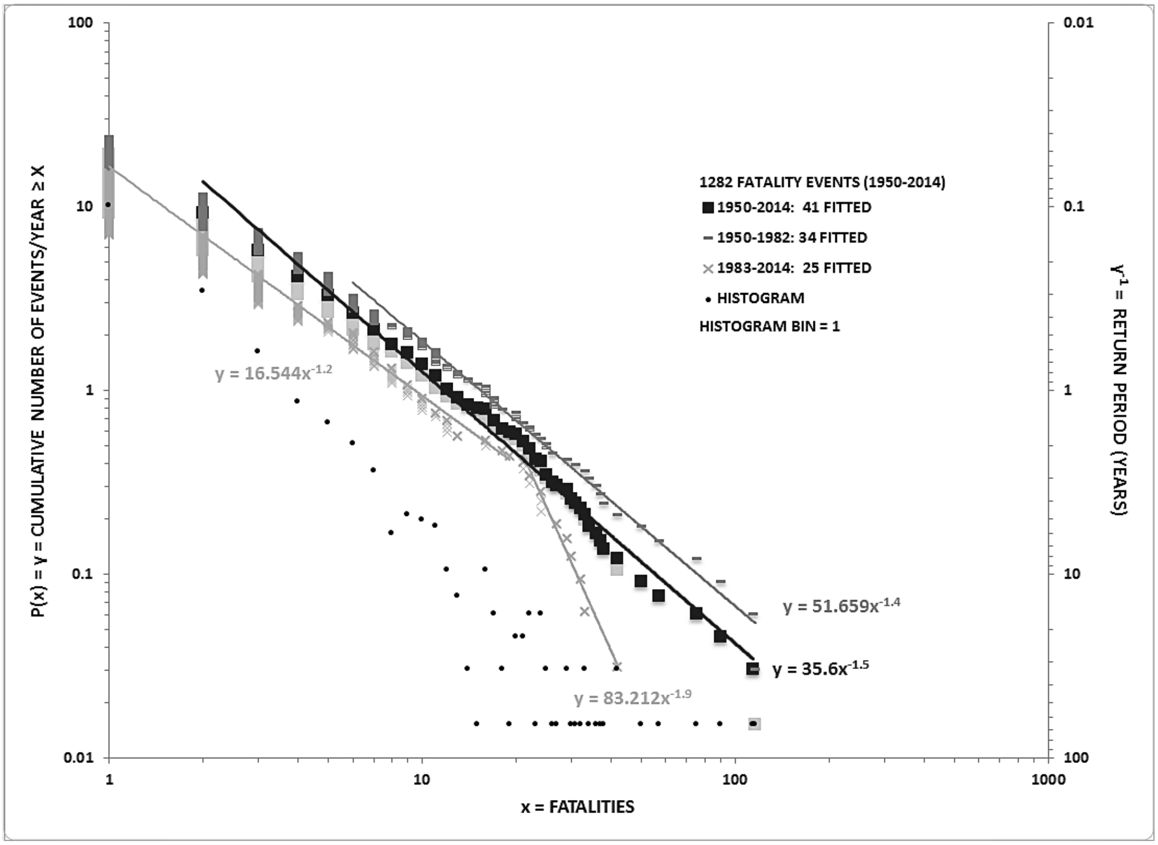


Figure E.6. Size-cumulative frequency plot of tornado fatalities for 1,282 of 46,402 individual events in the United States, 1900-2014. The data greater than 2 fatalities are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1950-1982 and 1983-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1 fatality.

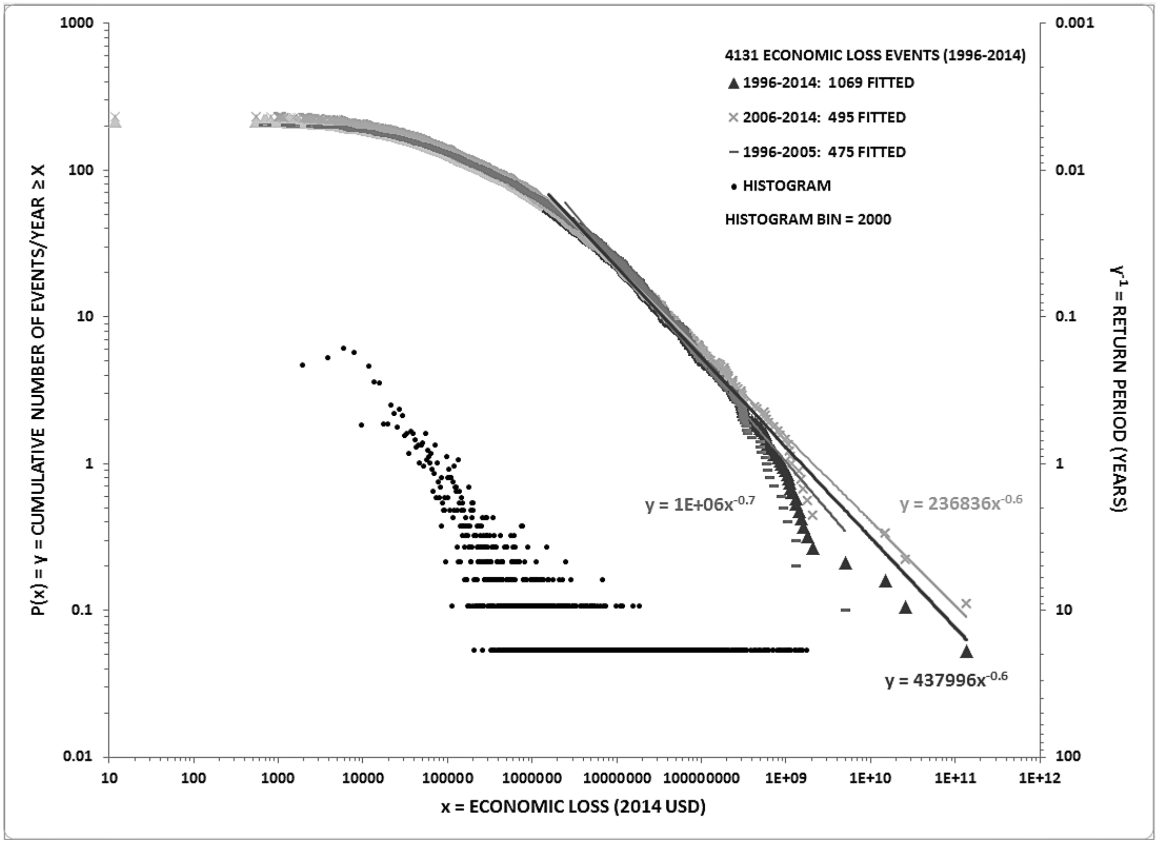


Figure E.7. Size-cumulative frequency plot of flood economic losses for 4,131 of 6,230 individual events in the United States, 1996-2014. The data greater than \$2 million are well fit by a power function. The x-axis is economic loss adjusted to 2014 USD. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1996-2005 and 2006-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is \$2,000.

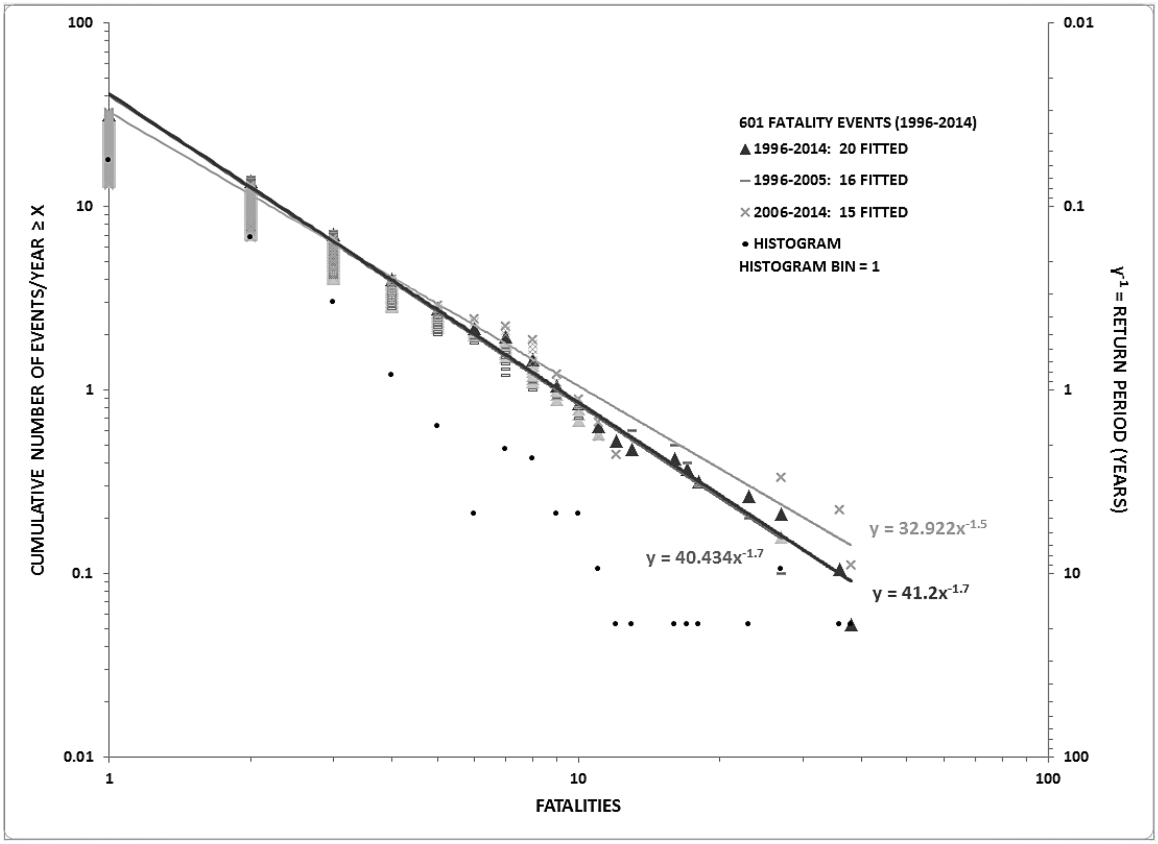


Figure E.8. Size-cumulative frequency plot of flood fatalities for 601 of 6,230 individual events in the United States, 1996-2014. The data greater than 1 fatality are well fit by a power function. The x-axis is number of fatalities. The left y-axis is cumulative number of events per year equal to and greater than x. The right y-axis is return period, in years, of an event equal to and greater than x. Separate halves of the data, 1996-2005 and 2006-2014, are each well fit by a power function. Histogram points are the upper-right corner of histogram bars for the non-cumulative frequency distribution of events. Histogram bin size is 1.

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