RESILIENT INFRASTRUCTURE
June 1–4, 2016

AN APPROACH TO CLASSIFICATION OF NATURAL DISASTERS BY SEVERITY

H. Jithamala Caldera
University of Calgary, Canada

S. C. Wirasinghe
University of Calgary, Canada

L. Zanzotto
University of Calgary, Canada

ABSTRACT

Existing scales for natural disasters describe severity in terms of intensity. Intensity scales are not highly correlated with impact factors such as fatalities, injuries, homelessness, affected population, and cost of damage. The descriptive words for disasters are also not sufficient to clearly comprehend the real magnitude of severity as there is no consistent method to distinguish one terminology from another. Further, data collection standards vary among countries and, therefore, comparisons across space and time are difficult to make. Several discrepancies between various sources of information complicate the interpretation of trends in disaster data. Furthermore, comparing different events and obtaining a sense of scale are problematic due to the deficiencies that reduce the quality of the data set, and disaster managers may face inconsistencies in identifying the magnitude of a disaster, responding to the event properly, and allocating resources for mitigation measures. There is no scale currently that is supported with data that can rate the severity of any natural disaster. This ongoing study attempts to develop a multidimensional scale. It also proposes a unified way of describing disasters by focusing on clear definitions, analyzing extreme events, and developing a set of criteria to make comparisons and rank natural disasters based on their impact, to help governments and relief agencies respond when disaster strikes. An initial severity scale based on fatalities is used to compare and rate disasters such as earthquake, tsunami, volcano and tornado. This concept can be applied to any type of disaster including windstorms, snowstorms, and wildfires.

Keywords: Natural Disasters; Disaster definitions; Classification; Severity; Impact of disasters

1. INTRODUCTION

Natural disasters come in all shapes and sizes ranging from a community fire to a large-scale tsunami. Currently, existing scales for natural disasters define severity levels in terms of intensity. Overall, intensity levels are in fact *not* the best way to describe the severity levels of a disaster because they are an indication only of the strength but not the impact of a disaster. The impact depends on where a disaster occurs, e.g. a populated city or rural area. In addition, there are different types of scales for different disasters: Earthquakes are measured using the Richter scale, volcanic eruptions using the VEI and Tornadoes using Enhanced Fujita Scale (EF-Scale). However, different types of disasters cannot be compared as there is no relationship between among different intensity scales. For example, comparing a Richter scale 7 earthquake with the VEI 7 volcanic eruption or with the EF scale 4 tornado impact is not possible. Therefore, a common method to compare different types of disasters is of interest.

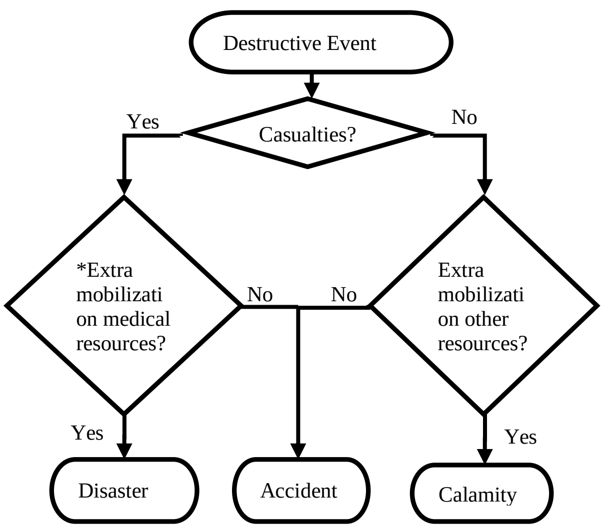
The descriptive terms for disasters are not sufficient to clearly distinguish the severity level. Natural events that cause fatalities, injuries and property damage are identified as emergencies, disasters, calamities, cataclysms, and catastrophes. Although these words have increasing levels of seriousness, one observer's "disaster" might be another's "catastrophe" or even "calamity" depending on personal feelings towards, and experience of, the event. In addition, almost all well-known dictionaries use one term to define another, and the words are used interchangeably.

Table 1: Definitions of disaster terms. Source; Oxford dictionary of English 3rd edn (Oxford University Press, 2010)

Emergency	Disaster	Catastrophe	Calamity	Cataclysm
A serious, unexpected, and often dangerous situation requiring immediate action.	A sudden accident or a natural catastrophe that causes great damage or loss of life.	An event causing great and usually sudden damage or suffering; a disaster.	An event causing great and often sudden damage or distress; a disaster.	A large-scale and violent event in the natural world.

For example the Oxford Dictionary describes a disaster as a catastrophe, and then defines catastrophes and calamities as disasters (Wirasinghe et al., 2013). The definitions of these terms according to the Oxford Dictionary are given in Table 1. Further, the vocabulary, context and interpretation of each term is not fixed (Kelman 2008) as the meaning of these words change over time.

Obtaining a sense of the real magnitude of a disaster's severity cannot be comprehended merely using the descriptive terms as there is no consistent method to distinguish one term from the other. In addition, the lack of a common terminology to identify the scale of the disaster is a major issue in disaster-related information management and processing (Hristidis et al. 2010). It can lead to "…inconsistent reliability and poor inter-operability of different disaster data compilation initiatives" (Below et al. 2009). In addition, comparing different events and obtaining a sense of scale are problematic due to the deficiencies that reduce the quality of the data set, and disaster managers may face inconsistencies in identifying a hazard potential, responding to the event properly, and allocating resources for mitigation measures (Gad-el-Hak 2008). Also, disaster compensation and insurance policies may not manifest a clear basis when there are deficiencies (Kelman 2008). These issues support the need to develop a consistent scale to understand the disaster continuum and develop a platform for reliable and transparent data management process that facilitates relative comparisons among various degrees of disasters (Löw & Wirtz 2010; Gad-el-Hak 2008).



*Depending on the medical severity Index

Figure 1: Algorithm following a destructive event

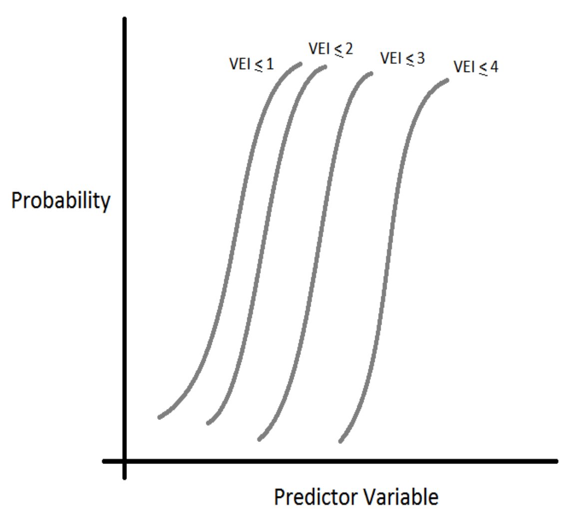


Figure 2: Example of proportional odds model which are parallel in ordinal logistic regression

As a foundation to the science of disaster medicine, de Boer (1990) tried to classify disasters as shown in Figure 1. He argued that if the destructive event has causalities and required extra mobilization of medical resources, then the event is classified as a disaster. On the other hand if the destructive event does not have any causalities but requires extra mobilization for other resources then it is classified as a calamity, otherwise they are accidents. Disaster scope has also been presented to differentiate the destructive capacity of a disaster by Gad-el-Hak (2008). As shown in Table 2, the disaster scope has five levels, which differentiate the severity of a disaster according to the number of displaced/ tormented/ injured/ killed people or the adversely affected area of the event. However, the ranges proposed for casualties and the area affected are arbitrary. Currently, there is no scale that is supported with data that can rate any natural disaster. As a solution to above mentioned inconsistencies, an initial scale based on fatalities is developed combined with clearly define terminologies to compare different types of disasters in terms of severity.

Table 2: Disaster scope. Source; Gad-el-Hak (2008)

Scope		Number of casualties		Geographic area affected
I	Small disaster	< 10	or	< 1 km2
II	Medium disaster	10 – 100	or	1 – 10 km2
III	Large disaster	100 – 1000	or	10 -100 km2
IV	Enormous disaster	1000 - 10000	or	100 – 1000 km2
V	Gargantuan disaster	>10000	or	>1000 km2

2. PRELIMINARY ANALYSIS

The severity of the impact of natural disasters increases with an increase in the impact to humans and their possessions and with an increase in intensity of an event for a given population density. Existing scales measure the destructive power of the disasters. If existing scales also demonstrate the severity of a given disaster, then there should be relationship between the existing scale and the impact parameters such as fatalities, injuries, economic damage. Otherwise, a different scale is mandated to measure the severity of a disaster.

The relationship between the available impact parameters with the existing scale have been studied using the data in National Oceanic and Atmospheric Administration (NOAA) database for different disasters. As shown in Table 3, impacts of a disaster is not highly correlated with the existing scales for volcano, earthquake, tsunami and tornado because all the correlation coefficients are less than 0.5. That means there is no evidence that there is a linear relationship between impact parameters and the existing intensity scale according to the available data. However, a nonlinear relationship between existing scales and impact factors can exist. This hypothesis is tested using 652 volcanic eruptions records from 4360 B.C. to 2014 A.D. in the NOAA database with five impact factors: number of fatalities, injuries, houses damaged, missing people and damage (in million dollars). Volcanic eruptions are measured using the VEI scale which is the best currently available factor that distinguishes one eruption from the other.

First, it is necessary to see whether there is a relationship between each impact factors before evaluating the relationship between VEI scale and the combination of impact factors. Spearman's rho correlation coefficient (ρ) is used to observe the correlation because all factors tested are ordinal variables. Table 4 shows the correlation coefficient (ρ) and the number of data points (N) used to calculate ρ for each pair of variable. Damage measured in million $ has a very good linear relationship with houses damaged (ρ=0.9). One variable (e.g. number of houses damaged) stayed in the model while the other (e.g. damage in million $) is omitted because of the high correlation. Damage in million $ has a close relationship with time and inflation, and thus hard to estimate. Hence it is omitted from the model. The Number of missing people and number of fatalities are also highly correlated (ρ=0.9). It can be observed that the number of pair wise data (N) used to evaluate ρ is fairly low with presence of missing number of people. It may explain the higher ρ value for some pairs. Therefore, the number of missing people is also omitted from the model. Other pairs, for example fatalities and houses damaged, are not highly correlated but have a moderate to good relationship ($0.5 \leq \rho < 0.75$). Therefore, fatalities, injuries and houses damaged is selected to see the relationship between impact factors and VEI scale. To find the relationships between VEI scale and other impact factors that represent the human impact of an eruption, ordinal logistic regression analysis is employed because the VEI is an ordinal categorical variable ranging from 0 to 8. In ordinal logistic regression it is assumed that each level of VEI is parallel to the other as shown in Figure 2. Different approaches have been tried to select a good relationship between VEI and the other variables. Some of the approaches are;

- Different link function (logit, probit, complementary log-log, negative log-log, Cauchit (inverse Cauchy))
    - The Link Function for the logit model is

[1] $$Log\left(\frac{\Pr obability(VEI \leq j)}{\Pr obability(VEI > j)}\right) = \alpha + \beta x$$; where j = 1, 2, …, 8 and α, β are regression parameters.

- Log transformation of fatalities, houses damaged, injuries
- Different periods
    - last 32 years (after 1982), after the VEI scale is introduced
    - last 114 years: after 1900, after a significant improvement in recording data
    - last 514 years: after 1500
- Include/ exclude interaction terms to the model (to address the multicollinearity effect)
    - Fatalities*Houses Damaged
    - Fatalities*Injuries

Table 3: correlation between intensity scales and impact factors

Disaster	Existing Scale	Fatalities	Injuries	Damage	House Destroyed	House Damaged	Missing
Volcano	VEI scale	0.33	0.39	0.09	0.33	-	0.45
Earthquake	Richter Scale	0.13	0.285	0.488	0.23	0.237	-
Tsunami	Intensity Scale	0.248	0.134	0.168	0.043	-	-
Tornado	EF Scale	0.339	0.366	0.32	-	-	-

Table 4: Spearman's rho correlation coefficient (ρ) and the number of data point (N) for volcanic effects variables

Variable	Missing		Injuries		Damage Million$		Houses Damaged	
	ρ	N	ρ	N	ρ	N	ρ	N
Fatalities	0.90	9	0.71	77	0.54	69	0.50	63
Missing			0.92	5	0.50	3	1.00	2
Injuries					0.64	22	0.54	28
Damage Million$							*0.90*	*53*

Table 5: P-values, criteria for each test and the Pseudo R-Square of individual ordinal logistic models

	Fatalities	Injuries	Houses Damaged	All p values
Test of Parallel Lines	0.171	0.801	0.825	>0.05
Goodness-of-Fit (Deviance)	0.105	0.685	0.888	>0.05
Model Fitting	0	0.001	0.003	<0.05
Pseudo R-Square (Cox and Snell)	0.131	0.152	0.113	-

    - Houses Damaged*Injuries
- VEI grouping (lack of data in lower and higher levels of VEI)
    - VEI (6,7,8->5)
    - VEI(0,1->1) and VEI(5,6,7,8->5)

Records of different periods has been analyzed to observe whether there is a difference between the sample before and after: 1900 that is after a significant improvement in recording data; and 1982 that is after the VEI scale was introduced. To select the best model (relationship) out of the above approaches three different hypothesis tests: tests of parallel lines (testing the assumption), goodness of fit tests, and overall model fits, have been conducted at the 95% confidence level.

Ordinal interval variables of fatalities, injuries and houses damaged individually have formed a good ordinal regression models with VEI. The best models are given when the link function is logit as shown in Equation 1; that is with the assumption that the residuals are logistically distributed, and some VEI are grouped (VEI 0,1 as VEI 1 and VEI 5,6,7,8 as VEI 5). P values for the tested hypotheses and the Pseudo R-Square values for models fatalities, injuries, and houses damaged individually with grouped VEI scale are showed in Table 5. Calculated p-values for the test of parallel lines and goodness of fit test are greater than 0.05 and the calculated p-values for model fitting is less than 0.05 for the models fatalities, injuries, and houses damaged individually with grouped VEI scale. Thus, the best three models are fatalities, injuries, and houses damaged individually with grouped VEI scale at 95%

confidence level. Table 6, shows the estimated parameters α (threshold) and β (location) in Equation 1 with corresponding p-values for the best selected models. All the p-values corresponding to the estimated parameters are less than 0.05 in fatalities and injuries models whereas, they are less than 0.1 in the houses damaged model. Hence, the estimated α and β in Equation 1 is suitable for the three models at 95% confidence level for fatalities, injuries and at 90% confidence level for houses damaged.

The results highlight the fact that individual variables of fatalities, injuries and houses damaged are better than the combinations of above variables, in explaining the relationship with VEI. Moreover, one variable become significant with the presence of another variable, because of multicollinearity between two variables (e.g. injuries become significant with the presence of fatalities, houses damaged become significant with the presence of fatalities and houses damaged become significant with the presence of injuries). Therefore, there might be evidence of an unexplainable component in this relationship. Prior experience, preparedness, awareness, evolving technology, mitigation methods, early warning systems and distance to the original event may minimize the number of fatalities

Table 6: Parameter Estimates for volcano effects categorised data

		Fatalities		Injuries		Houses Damaged	
		Estimate	P-value	Estimate	P-value	Estimate	P-value
Threshold (α)	VEI 1	-1.312	.000	-1.353	.021	-1.440	.037
	VEI 2	.869	.000	1.024	.029	.991	.090
	VEI 3	2.559	.000	2.948	.000	2.515	.000
	VEI 4	4.211	.000	4.918	.000	4.130	.000
Location (β)		.706	.000	.906	.001	.706	.004

and injuries although, the magnitude and the intensity of a disaster, may maximize the impact. The multicollinearity effect remains the same for all applied approaches hence the combination of impact variables could not be achieved as expected. Therefore, the results shows that VEI scale can only partially evaluate the severity which means a scale is required to compare the impact of same disaster and well as to compare different disasters.

3. INITIAL SEVERITY SCALE

The impact of disasters on people, facilities, and the economy should be studied in detail to understand the severity of a natural disaster. The factors, such as the number of fatalities, injuries, homelessness, affected population, affected area, and cost of damage can be considered for a multi-dimensional scale which may provide a technique to compare and contrast the impacts of different types of disasters. A one dimensional scale based on fatalities is introduced as follows as an initial step.

Extreme value theory helps to study the behavior and the destructive capacity of strong, violent uncontrollable disasters which are infrequent. Three different methods, block maxima, R^{th} order statistics, and threshold, can be used to determine the extreme values from a given data set. Extremes are placed in the tail end of the parent probability distributions and in this case, the right tail end as the considered extremes are maxima or severe events. An extreme value distribution (EVD) is essential to evaluate the probability of extreme disasters.

To understand the disaster continuum, a global level dataset with different types of natural events should be considered. Therefore, ten different type of disasters; large scale global disasters such as earthquakes, tsunamis, and volcanoes, regional scale disasters such as floods, cyclones, and tornadoes, and local scale disasters such as flash floods, forest fires, landslides and lightning, are included in the study. Block maxima method is not suitable because it do not give enough data for the analysis and threshold method is not suitable because the extremes which exceed some threshold value only consider the large scale disasters but not small scale extremes such as lightning. Therefore, R^{th} order statistic is used for the extreme value analysis to understand the full range of severity. To develop a fatality based scale by reflecting the reasonable amount of data from each type of disaster, the 10^{th} order statistic is selected. Records of fatalities in the top ten extreme cases for each disaster type are taken as one dataset for this purpose. However, only the most extreme seven lightning fatalities were considered because the dataset consists of natural events that cause at least one fatality. The mean and the standard deviation of the 97 disaster data for fatalities is 112,135 and 290,807. Figure 3 shows the histogram of fatalities and the best fitted Weibull distribution (Equation 2) plotted in the same graph.

[2] $$F(x) = 1 - e^{-\left(\frac{x}{37496}\right)^{0.4095}}$$

Table 7 shows the introduced fatality based disaster scale with ten different levels to differentiate the severity of a disaster. The magnitude of an impact of a disaster is evaluated based on the logarithm of the fatalities. Logarithm or the base 10 is selected to differentiate the severity levels, intervals, ranges or boundaries for all types of natural disasters in the fatality based disaster scale because the probability of a very high classification is low for severe natural disasters as the events are rare. More severe disasters have a higher classification according to the logarithmic scale, therefore, an increase in the severity ranges by power of 10, as the level increases in the fatality based disaster scale, can be justified by the fact that the probability of such events is rare. In addition, the base 10 measurement is easy to remember and meaningful to differentiate one severity level from the other. Therefore, the severity levels in Table 7 introduce a way to measure the severity of a natural disaster. The sample probabilities as well as expected probabilities which are evaluated using Equation 2, are shown in Table 7. The ten levels, or categories, are labeled with commonly used terms that describe various magnitudes of a disaster from emergency to cataclysm. The proposed definitions of these terms: emergency, disaster, catastrophe, calamity and cataclysm in the

Table 7: Fatality based disaster scale. Source; Caldera & Wirasinghe (2014)

Type	Fatality Range	Sample Probability	Expected Probability	Example
Emergency	$1 \leq F < 10$	0	0.021	A small landslide that kills one person
Disaster Type 1	$10 \leq F < 100$	0.031	0.051	Edmonton tornado, Canada - 1987 - 27 deaths
Disaster Type 2	$100 \leq F < 1,000$	0.268	0.118	Thailand flood – 2011 - 815 deaths
Catastrophe Type 1	$1,000 \leq F < 10,000$	0.175	0.238	Hurricane Katrina, USA – 2005 - 1833 deaths
Catastrophe Type 2	$10,000 \leq F < 0.1M$	0.216	0.334	Tohuku earthquake and tsunami, Japan - 2011 - 15882 deaths
Calamity Type 1	$0.1M \leq F < 1M$	0.299	0.203	Haiti earthquake - 2010 – 316.000 deaths
Calamity Type 2	$1M \leq F < 10M$	0.010	0.022	China floods - 1931 – more than 2,500,000 deaths
Cataclysm Type 1	$10M \leq F < 100M$	0	$5.27*10^{-05}$	Black death pandemic - from 1346 to 1353
Cataclysm Type 2	$100M \leq F < 1B$	0	$1.04*10^{-11}$	Super Volcano (e.g. Yellowstone) – less than 1 billion estimated deaths
Partial or Full Extinction	$1B \leq F < 10B$	0	0	Meteor strike (diameter > 1.5 Km) - less than 1.5 billion estimated deaths Pandemic (Avian influenza) – less than 2.8 billion estimated deaths

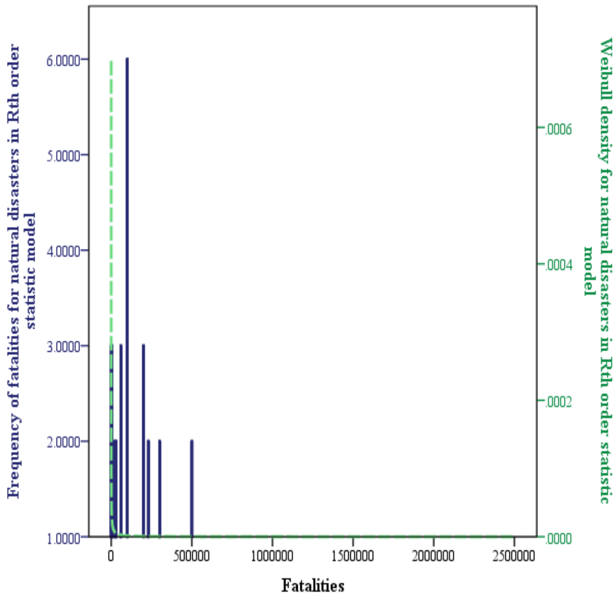


Figure 3: Histogram of extreme fatalities for ten different natural events and the fitted Weibull distribution

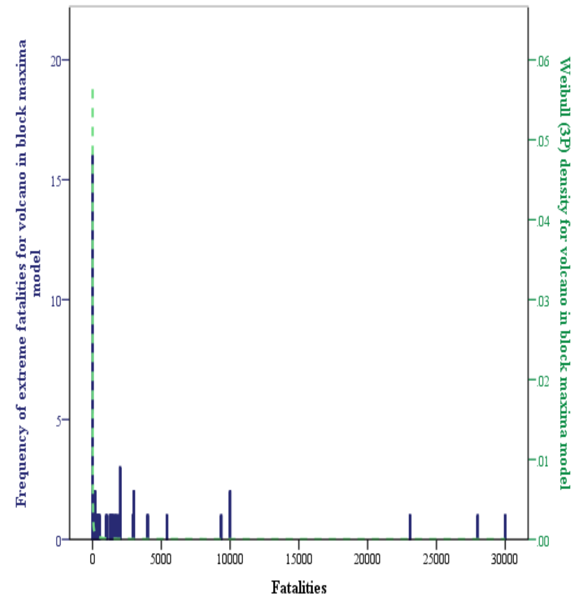


Figure 4: Histogram of extreme fatalities for volcano in block maxima model and the fitted density

In Table 7 types of events are defined according to the following definitions for the existing terminologies on the basis of dictionary and commonly accepted understandings. However, using any combination of four of the five words to describe a fifth word is carefully avoided. The ordering from lowest to highest in Table 7 is taken into consideration, rather than relying on the five words to describe each other. There is an increasing level of seriousness as indicated in the definition of the terms using the following methods of designation: to describe circumstance, from lowest to highest, 'event', 'disturbance', 'upheaval'; to describe the impact, from lowest to highest, 'damage', 'destruction', 'devastation'; to describe the injuries, from lowest to highest, 'serious', 'major', 'massive', 'uncountable'; and to describe the fatalities from lowest to highest, 'many', 'extensive', 'great', 'unimaginable'.

- EMERGENCY: A sudden natural event that causes damage, injuries and some fatalities

Table 8: Disaster Classification

Type	Flash Flood	Forest Fire	Lightning	Tornado	Volcano	Land slide	Cyclone/ Hurricane	Earthquake	Tsunami	Flood
Emergency	√	√	√	√	√	√	√	√	√	√
Disaster Type 1	√	√	√	√	√	√	√	√	√	√
Disaster Type 2	√	√	√	√	√	√	√	√	√	√
Catastrophe Type 1	√	√	√	√	√	√	√	√	√	√
Catastrophe Type 2	×	×	×	×	√	√	√	√	√	√
Calamity Type 1	×	×	×	×	×	√	√	√	√	√
Calamity Type 2	×	×	×	×	×	×	×	×	×	√
Cataclysm Type 1	×	×	×	×	×	×	×	×	×	×
Cataclysm Type 1	×	×	×	×	×	×	×	×	×	×
Partial or Full Extinction	×	×	×	×	×	×	×	×	×	×

- DISASTER: A major natural event that causes significant damage, and many serious injuries and fatalities
- CATASTROPHE: A large scale natural disturbance that causes severe destruction, major amount of injuries and extensive fatalities
- CALAMITY: A very large scale natural disturbance that causes widespread destruction, massive amount of injuries and a great loss of life

- CATACLYSM: An extremely large scale natural upheaval, that causes widespread devastation, uncountable amount of injuries and unimaginable loss of life

The minimum level of the scale, ‘emergency’ is the situation when there is at least one fatality and less than ten fatalities. The highest level ‘Partial or Full Extinction’ is defined when there are fatalities exceeding one billion. The severity level of the most extreme disaster that occurred, and for which data is available, is categorized as Calamity Type 2, however, a Cataclysm Type 1 or 2 disaster with very small probability is expected according to Table 7. The disasters such as meteoroid impact has the potential to vary from emergency to the partial or full extinction although there is no historical data record. Its range can go from a small meteor strike that explodes in the atmosphere to a large asteroid that falls to the earth causing unimaginable impacts. Table 8 illustrate the levels covered by each disaster indicated as ’√’ and the levels not covered indicated as ‘x’. In Table 8, the list of disasters has been ordered to show the increasing coverage of the scale. According to this classification, local disasters such as flash flood, lightning cover the lower levels whereas the disasters with potential regional or global level impacts cover upper levels. A flood has the ability to reach the calamity Type 2 level. Local disasters such as flash flood, forest fire, lightning and tornadoes go up to the catastrophe Type-1 level.

3.1 Separate analysis for each disaster

By using the above fatality based disaster scale, separate analysis for earthquake, tornadoes, tsunamis and volcanoes has been done. The volcano disaster is selected to demonstrate the separate analysis for each type of disaster. There are 236 volcanoes in the NOAA database which have at least one eruption.

3.1.1 Block maxima model

In the block maxima method each volcano is considered as one block and the full lifetime of the volcano is considered as the width of each block. Therefore, only the maximum fatality recorded for each volcano is considered for extreme value data analysis. For instance, in the volcanic effects for the Mount Tombora 1815 eruption record 10,000 fatalities, Mount Krakatoa, 1883 eruption record 2,000 fatalities. All the records which do not have at least one fatality are not considered because the fatality data which are blank in the database either represent no fatality or no record found. Accordingly, extreme fatality recorded eruptions for 136 volcanoes are shown to be distributed as a 3 parameter Weibull (α=0.33925, μ= 1, σ= 109.04) distribution (Equation 3) with sample mean 1202.81, sample variance 4251.75 and the maximum 30,000. Figure 4 shows the histogram of the extreme fatality volcano effects and the fitted Weibull (3P) density (dashed line). R^{th} order statistic method is not used in the volcano study because there are enough data (136) for the extreme fatality analysis.

[3] $F(x) = 1 - e^{-\left(\frac{x-1}{109.04}\right)^{0.33925}}$

3.1.2 Threshold model

Usually, a mean residual plot aids to estimate the threshold, u_0. For u> u_0, E(X-u/ X>u) is a linear function of u and E(X-u/ X>u) is the mean of the values that exceed the threshold, u, for which the sample mean of the threshold values above u provides an empirical estimate. These estimates are expected to change the linearity of E(X-u/ X>u) at some value of u along the u-axis. The value of u at which linearity changes is the suitable threshold value for which the generalized Pareto model is appropriate (Coles 2001). The mean residual plot equals $\left\{\left[u, \frac{1}{n_u}\sum_{i=1}^{n_u}\left(x_{(i)} - u\right)\right] : u < x_{\max}\right\}$, where x(1), …x($n_u$) consists of the n_u observations that exceed u. Figure 5 shows the mean residual plot for the number of fatalities. The graph is approximately linear from u=0 to u ≈ 153, beyond which it is appears to curve until u ≈ 10,000, whereupon it decays sharply. It is tempting to conclude that there is no stability until u = 10,000, after there is approximate linearity. Thus suggest u_0 = 10,000, however, there are just three exceedances of the threshold u = 10000, too few data to make meaningful inferences. Moreover, the information in the plot for large values of u is unreliable due to the limited amount of data on which the estimate and are based. The second procedure for threshold selection is to estimate the threshold value approximately equaling it to $1.5\sqrt{n}$ as suggested by Hasofer (1996). Accordingly, threshold set at u_0 = 26.28 where there are 307 eruption records which has at least one fatality. There are 113 volcano eruptions exceed 26 fatalities and follow the Pareto distribution with a shape parameter (α) = 0.41937, and scale parameter (σ) = 27 as shown in equation 4.

[4] $F(x) = 1 - \left(\frac{27}{x}\right)^{0.41937}$

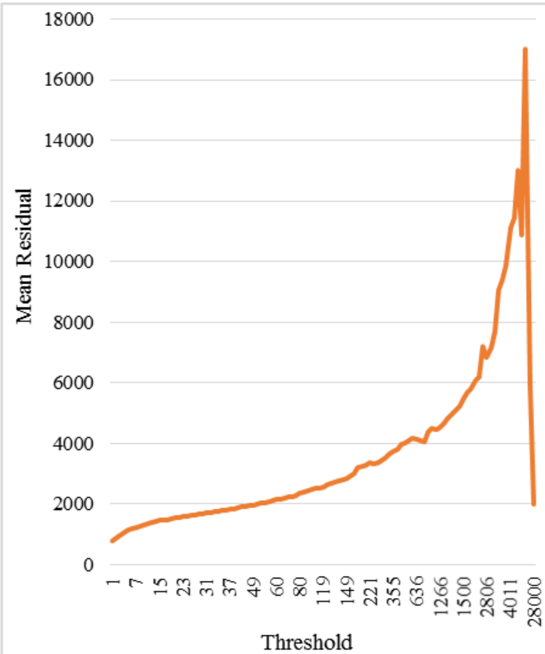


Figure 5: Mean residual plot

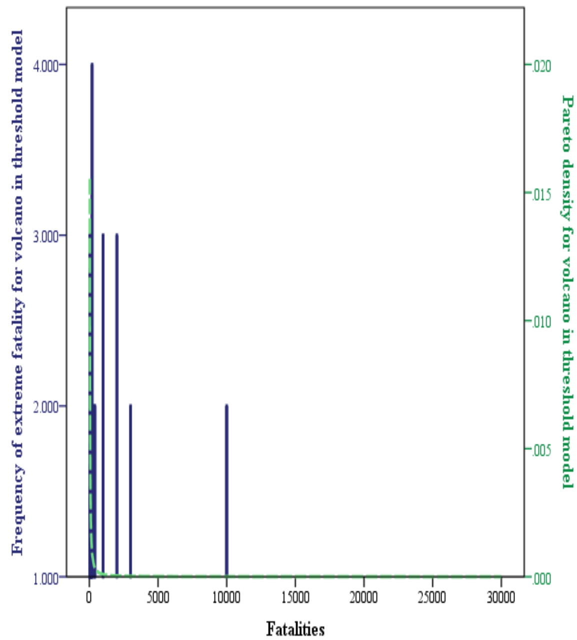


Figure 6: Histogram of extreme fatalities for volcano effects and the fitted Pareto density (dash line).

<u>3.1.3 Estimated probabilities for severity levels of volcano</u>

According to the fatality based disaster scale severity boundaries given in Table 7, the estimated probabilities of extreme volcano eruptions are calculated using the best fitted Weibull distribution and Pareto distribution as shown in Table 9. Sample probabilities of volcano disaster are also calculated for severity levels of fatality based disaster scale using the 307 eruption records which has at least one fatality. The severity level of the most extreme volcanic eruption for which data is available (450 A.D. -Ilopango, El Salvador, 30,000 fatalities) can be categorized as Catastrophe Type 2. However, expected probabilities indicate that volcanic eruptions can be even more destructive, for example, 4 in 100,000 eruptions have the ability to reach the calamity type 1 or higher according to the fitted Weibull distribution, whereas the estimate is 3 in 100 according to the fitted Pareto distribution. Note that the

Table 9. Probability of an eruption to be of the given type

Type	Fatality Range	Sample probability	Expected Probability		Example
			Block Maxima	Threshold	
Emergency	1 ≤ F < 10	0.531	0.35	-	Nabro volcano, Eritrea (2011) – 7 deaths
Disaster Type 1	10 ≤ F < 100	0.225	0.27	0.423*	Marapi volcano, Indonesia (1975) – 80 deaths
Disaster Type 2	100 ≤ F < 1,000	0.130	0.26	0.358	Pinatubo volcano, Philippines (1991) – 450 deaths
Catastrophe Type 1	1,000 ≤ F < 10,000	0.098	0.11	0.136	Lamington volcano, Papua New Guinea (1951) – 2942 deaths
Catastrophe Type 2	10,000 ≤ F < 100,000	0.0163	0.01	0.052	Ruiz volcano, Colombia (1985) – 23080 deaths
Calamity Type 1 and higher	100,000 ≤ F < 1M	0	0.00004	0.032	-

*27 ≤ F < 100

probabilities calculated according to the fitted extreme value distributions, are conditional probabilities given a volcanic eruption recorded with at least one fatality. Volcanic eruptions can vary from emergency to the Catastrophe Type 2 level. However, an unusual large (super volcanic) eruption has the potential to exceed the above mentioned levels. They can possibly cause a calamity or even a partial or full extinction. Expected Pareto probability is higher than the expected Weibull probabilities as it consider all the eruptions which have more than 26 fatalities. In contrast, Weibull distribution has the full range of expected fatalities although it does not consider all the extreme fatality records. Weibull probabilities are closer to sample probabilities than Pareto probabilities. According to the fitted Weibull distribution for volcanic eruptions, 35 percent of the eruptions are the Emergency type, 27% and 26% eruptions are Disaster type 1 and 2 respectively, 11% and 1% eruptions are Catastrophe type 1 and 2 respectively, as shown in Table 9.

3.2 Combined analysis

Extreme fatality analysis is conducted for earthquake, tsunami and tornado disasters as well, similar to the above volcano eruption extreme fatality analysis. By considering block maxima and threshold models, the probabilities of extreme disaster events are calculated for the severity levels introduced in fatality based disaster scale. Table 10 shows the summarized version of the obtained probabilities for expected extreme volcanoes, earthquakes, tsunamis and tornadoes. According to the block maxima method, both earthquakes and tsunamis have 0.2% probability for calamity type 2 or higher events. In other words 2 in 1000 extreme tsunamis or earthquakes can have more than 1 million fatalities, although there are no historical events. Extreme tsunamis have the highest probability to be the calamity type 2 compared to volcano, earthquake and tornado according to the threshold model which consider the all the worst disaster records. In contrast, tornado has the least probability 0.01% to be Catastrophe Type 2 compared to worst disaster records of volcanoes, earthquake and tsunamis because they are local events.

Table 10: Expected probabilities of volcano, earthquake, tsunami and tornado based on block maxima model

Type	Fatality Range	Volcano		Earthquake		Tsunami		Tornado	
		Weibull	Pareto	Weibull	Pareto	Weibull	Pareto	Weibull	Pareto
Emergency	$1 \leq F < 10$	0.35	-	0.24		0.11		0.74	0.949
Disaster Type 1	$10 \leq F < 100$	0.27	0.423*	0.13		0.14		0.14	0.045
Disaster Type 2	$100 \leq F < 1000$	0.26	0.358	0.16		0.26		0.01	0.005
Catastrophe Type 1	$1000 \leq F < 10000$	0.11	0.136	0.24		0.32	77.7#	$8*10^{-4}$	0.001
Catastrophe Type 2	$10000 \leq F <0.1M$	0.01	0.052	0.18	0.817ǂ	0.16	19.7	$6*10^{-5}$ [a]	$1*10^{-4}$ [a]
Calamity Type 1	$0.1M \leq F < 1M$	$4*10^{-5}$	0.02	0.05	0.176	0.01	2.3		
Calamity Type 2 and higher	$1M \leq F$	0	0.012	0.002	0.007	0.002	0.27		

*$27 \leq F < 100$; ǂ$30000 \leq F < 100000$; and #$2000 \leq F < 10000$; [a] Catastrophe Type 2 and higher

4. DISCUSSION

Three different models: block maxima, R^{th} order statistic, and threshold methods are used to analyse extreme natural disasters based on fatalities for the purpose of determining a severity scale and classification. Depending on the application, different models are suitable. For example, block maxima estimated probabilities based on a country is useful to evaluate the probability of the worst tsunami that local authorities/governments should consider for preparation, while block maxima or R^{th} order statistic based on location is useful to evaluate the probability of the worst tsunami during the next 150 years that planners should consider.

By using the above fatality based disaster scale introduced in Table 10 and disaster classification in Table 8, it is easy to compare and contrast volcanoes, earthquakes, tsunamis and tornadoes. The same concept can be applied to any type of disaster including windstorms, convective storms, snowstorms, and wildfires. Moreover, by having the expected probabilities according to the historical disasters, disaster managers and emergency respondent personal can have a clear sense of scale about the severity of each type of disasters. This knowledge can be used to deploy the resources as needed when disaster strikes.

5. CONCLUTION

This study provides an overall picture of the severity of natural disasters, as well as a set of criteria used to make comparisons for all types of disasters and to rank them to help governments and relief agencies respond quickly when disaster strikes. This is an ongoing research project to develop a multidimensional scale to understand the disaster continuum.

ACKNOWLEDGEMENTS

This research is supported in part by the University of Calgary. The Schulich School of Engineering Activity Fund and the University Research Grants Committee provided support to attend the Third United Nations World Conference on Disaster Risk Reduction.

REFERENCES

Below, R., Wirtz, A. & GUHA-SAPIR, D., 2009. *Disaster Category Classification and peril Terminology for Operational Purposes*, Brussels. Available at: http://www.cred.be/publication/disaster-category-classification-and-peril-terminology-operational-purposes.

Caldera, H. J. & Wirasinghe, S.C., 2014. Analysis and Classification of Volcanic Eruptions. In R. R. Rapp & W. Harland, eds. *The 10th International Conference of the International Institute for Infrastructure Resilience and Reconstruction (I3R2)*. West Lafayette, Indiana: Purdue University., pp. 20–22.

Coles, S., 2001. *An Introduction to Statistical Modeling of Extreme Values*, Springer, London.

de Boer, J., 1990. Definition and classification of disasters: Introduction of a disaster severity scale. *The Journal of Emergency Medicine*, 8(5):591–595.

Gad-el-Hak, M., 2008. The art and science of large-scale disasters. In M. Gad-el-Hak, ed. *Large-Scale Disasters*. Cambridge: Cambridge University Press, pp. 5–68.

Hasofer, A.M., 1996. Non-parametric Estimation of Failure Probabilities. In F. Casciati & B. Roberts, eds. *Mathematical models for structural reliability analysis*. CRC Press, pp. 195–226.

Hristidis, V., Chen, S.-C., Li, T., Luis, S., & Deng, Y., 2010. Survey of data management and analysis in disaster situations. *Journal of Systems and Software*, 83(10):1701–1714.

Kelman, I., 2008. Addressing the root causes of large-scale disasters. In M. Gad-el-Hak, ed. *Large-Scale Disasters*. New York: Cambridge University Press, pp. 94–119.

Löw, P. & Wirtz, A., 2010. Structure and needs of global loss databases of natural disasters. In *International Disaster and Risk Conference IDRC*. Davos, Switzerland, pp. 1–4.

Oxford Dictionary of English, 3rd edn, 2010. Stevenson, A., ed. Oxford University Press, Oxford.

Wirasinghe, S.C., Caldera, H. J., Durage, S. W., & Ruwanpura, J. Y., 2013. Preliminary Analysis and Classification of Natural Disasters. In P. H. Barnes & A. Goonetilleke, eds. *The 9th Annual International Conference of the International Institute for Infrastructure Renewal and Reconstruction*. Brisbane, Queensland, Australia: Queensland University of Technology, p. 11.