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A Global Expected Risk Analysis of Fatalities, Injuries, and Damages by Natural Disasters

Guoqiang Shen [1,2], Long Zhou [2,*], Yao Wu [2,3] and Zhiming Cai [2]

1 College of Architecture, Planning and Public Affairs, University of Texas at Arlington, Arlington, TX 76019, USA; guoqiang.shen@uta.edu
2 Faculty of Urban Management and Studies, City University of Macau, Taipa, Macau 999078, China; ywu@cityu.mo (Y.W.); caizhiming@cityu.mo (Z.C.)
3 College of Design, Jiangnan University, Wuxi 214122, China
* Correspondence: lzhou@cityu.mo; Tel.: +853-85902862

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Abstract: Natural disasters are hazardous geophysical, meteorological, hydrological, climatological, and/or biological events that disturb human and natural environments, causing injuries, casualties, property damages, and business interruptions. Sound analysis is required regarding the effective hazard preparedness for, response to, mitigation of, and recovery from natural disasters. This research proposes an expected risk analysis model of world natural disasters recorded for 1900–2015 in the Emergency Disaster Database compiled by the Centre for Research on the Epidemiology of Disaster. The model produces consistent estimates of country-level risks in terms of human casualty and economic loss. The expected risks, along with their standard deviations, and ranks for world 208 countries, are analyzed with highlights for the top 10, 20 and 30 countries. Normalized expected risks by country population density and per capita gross domestic product (GDP) are also analyzed to further understand the relationships between risks and socio-economic measures. The results show that the model is a reasonably effective alternative to the existing risk analysis methods, based on the high correlations between the observed and estimated total risks. While riskier countries with higher expected risks and standard deviations are found in all continents, some developing countries such as China, India, Bangladesh, and Brazil, or developed countries, such as the United States, Japan, and Germany, are the hot-spots of global natural disasters. The model can be used as a new alternative approach to conduct country-level risk assessments or risk analyses of fatality, injured, affected, and damage—especially for countries' governments to make sound disaster preparation, and mitigation decisions, sustainable policies, or plans regarding natural disasters.

Keywords: natural disaster; expected risk modelling; human casualty; economic loss; country-level

1. Introduction

Natural hazards occur frequently around the world. Some natural hazards turn into disasters after they cause tangible (or physical) impact, such as human fatalities and property damages; and intangible (non-physical) impacts, such as psychological, mental, and political wounds [1]. Research has shown that human casualties and economic losses due to natural disasters have been increasing over the last five decades [2,3]. This trend is likely to continue due to growing urbanization, rising populations, deepening industrialization, and worsening global environmental and climate change [4]. For example, from 1950 to 1979, 1779 natural disasters occurred across the world, causing 4,860,449 casualties, 1,372,606 injuries, and $78 billion in property damages. However, from 1980 to 2015 the reported number of natural disasters increased to 11,494 or about 6.5 times as many as those in the period of 1950–1979: Causing 2,599,237 fatalities, 6,354,195 injuries and $2.71 trillion in property damages [5].

In order to effectively prepare for, respond to, and recover from natural disasters, good hazard risks and assessments at various spatial and temporal scales are essential [6,7]. This research proposes and applies a new quantitative model to assess physical impacts of world natural disasters as risks at the country-level, using the international Emergency Disaster Database (EM-DAT)—compiled by the Centre for Research on the Epidemiology of Disaster (CRED) [8]. The model takes country-specific posterior data on natural disasters for the period of 1900–2015, including disaster occurrences, classifications, and disaster impacts, and produces disaster risk estimates, rankings, and correlations to country socio-economic attributes. The proposed model is validated by Pearson and Spearman correlations, for the values and ranks of the estimated and observed total disaster impacts. The country-level risk assessment may be coarse due to using 'country' as the spatial unit, especially for large countries in which intra-country variability may be quite high. However, it is still worthy to reveal inter-country differences, especially global hot-spots, in risk impacts for historically reported natural disasters in the world. A comparative global risk analysis provides useful insights for country-specific or global humanitarian policies toward minimizing natural disaster impacts, and promoting sustainable development. Perhaps more importantly, as the literature review section illustrates below, while various sub-country spatial scales have been used [1], using country as the spatial scale is relatively rare in disaster risk research [4,5], especially from the global country comparative perspective for multiple natural disasters over the previous 115 years.

2. Literature Review

2.1. Hazards, Disasters, and Risks

A hazard is an extreme and severe event, that could potentially pose a risk to human beings and their settlements [9,10]. According to CRED, natural hazards are classified into geophysical, meteorological, hydrological, climatological, and biological categories in Table 1. Geophysical hazards take the forms of earthquakes, tsunamis, mass movement, and volcanic eruptions. Meteorological hazards are storms, extreme temperature, and fogs. Climatological hazards consist of drought, glacial lake outbursts, and wildfires. Hydrological hazards include floods, landslides, and wave actions. Finally, biological hazards contain epidemics, insect infestation, and animal accidents. This research focuses on these five natural disasters, and their physical impacts or risks: Fatality, injured, affected, and damage—as defined in CRED and summarized in Table 1.

2.2. Risk and Risk Assessment Models

While global natural disaster databases, such as EM-DAT, are vital, the stochastic nature of hazard occurrences and impacts make a reliable risk assessment essential for decision makers. They help formulate and adopt risk-related policies, as well as assist emergency planners and professionals to effectively and efficiently mitigate disasters. Smith [11] defines risk as probability of a specific hazard occurrence. Likewise, Cooney [12] describes risk as function of probability and magnitude of different impacts. In general, a risk analysis for a location starts with the area's historical hazards, disasters, and impacts. Risk analysis involves risk determination, which is to identify the types of hazards and measure their potential risk levels in terms of disaster impacts [13,14].

Various descriptive or quantitative risk models of natural hazards exist in the literature, including risk/hazards approach [15]; political ecology approach [16]; pressure and release approach [17]; hazard-of-place approach [18]; and vulnerability/sustainability approach [19]. Furthermore, a spatial risk model was developed by Shen and Hwang [20]; a exposure model of global natural hazards by Bono and Mora [21]; a macro framework for measuring vulnerability by Joseph [22]; a natural hazard geoportal by Giuliani and Peduzzi [23]; a global risk index model by Peduzzi et al. [24]; a global natural disaster risk model by Dilley et al. [25]' a mapping of global hazard datasets by Peduzzi and Herold [26]; and a global natural disaster assessment model by Berke [27].

Table 1. Definition and classification of natural hazards and impacts of natural disasters.

Hazard	Classification	Definition	Disaster Type
Natural Hazard Types	Geophysical	A hazard originating from solid earth. This term is used interchangeably with the term geological hazard.	Earthquake, mass movement, volcanic activity
	Meteorological	A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days.	Extreme temperature, fog, storm
	Hydrological	A hazard caused by the occurrence, movement, and distribution of surface and subsurface freshwater and saltwater.	Flood, landslide, wave action
	Climatological	A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability.	Drought, extreme temperature, glacial lake outburst, wildfire
	Biological	A hazard caused by the exposure to living organisms and their toxic substances (e.g., venom, mold), or vector-borne diseases that they may carry. Examples are venomous wildlife and insects, poisonous plants, and mosquitoes carrying disease-causing agents such as parasites, bacteria, or viruses (e.g., malaria).	Epidemic, insect infestation, animal accident
Term	**Definition**		
Fatality	Number of people who lost their life because of natural hazards		
Injured	People suffering from physical injuries, trauma or an illness requiring medical treatment as a direct consequence of a disaster.		
Affected	Sum of injured, homeless (number of people whose house is destroyed or heavily damaged and therefore need shelter after an event), and affected (people requiring immediate assistance during a period of emergency).		
Damage	The amount of damage to property, crops, and livestock. In the Emergency Disaster Database (EM-DAT) estimated damages are given in US$ ('000). For individual disaster, the registered figure corresponds to the damage value at the moment of the event.		

Liu et al. [28] documented the quantitative models mostly for global hazard risk analysis, including the risk index approach and the mathematical statistics approach. These approaches are mostly based on statistics and spatial analysis, and hence, can be used to index, rank, estimate or predict hazard risks. More extensive discussions on analytical risk models and frameworks can be found in Cox [29], Schmidt et al. [30] and Greenberg and Cox [31]. Some mitigation-based research for specific disasters can be found in Masuya et al. [32] on shelter-residence match for flood evaluation; Sohn et al. [33] on cost-benefit of retrofitting a transportation network under an earthquake; and Shen and Aydin [34] on reconstruction schedules for high freight flow movement after hurricane Katrina.

However, the applications of these quantitative hazard models either focus on a country or a region of the world. Our literature review indicates that there is a lack of risk assessment of natural disasters at the global scale, especially from a comparison and contrast perspective for multiple physical impacts over time. Therefore, this research aims to fill this gap by examining global risks based on country-level fatalities, injuries, people affected, and damages caused by natural disasters of the world from 1900–2015. A country-level risk assessment may be coarse, especially for large countries (in which intra-country variability may be quite high), but it is still reveals inter-country differences—especially regarding global hot-spots—in risk impacts for historically reported natural disasters in the world. Such a comparative global risk analysis also provides useful insights for country-specific or global humanitarian policies toward minimizing natural disaster impacts, and sustainable development.

3. Methods and Materials

The methodology consists of a set of notations in Figure 1 and a risk assessment model, in which we consider country k as the spatial unit, and hazard occurrences i for the natural disaster group $m = 1$. This includes sub-groups g, with each resulting in some disaster impacts j, including fatality, injury, affected, and damage. Note that the model collapses all time units (e.g., year) into the 1900–2015 period. Therefore, the model primarily is a spatial one for estimating cumulative expected risks for countries based on multiple impacts. Although disasters happen seemingly randomly, the model does not consider temporal variations, nor spatial variations within country over the period. The model's main purpose is to estimate country-level expected risks in fatalities, injuries, people affected, and economic damages.

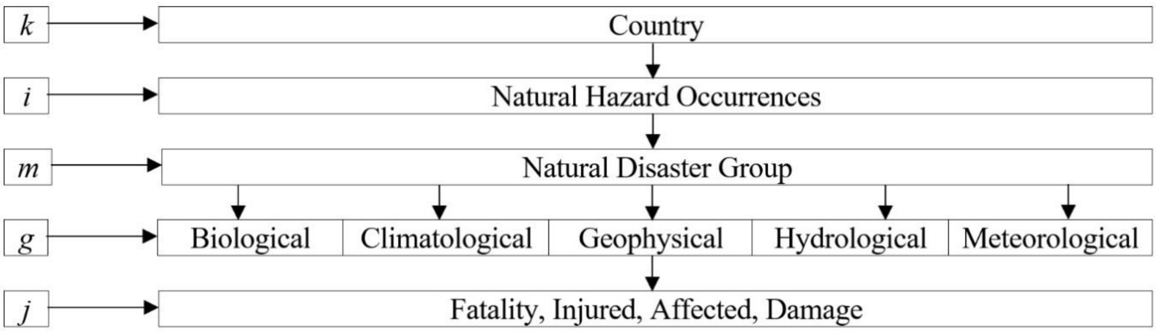

Figure 1. Modelling process and notation.

3.1. Expected Risk Model

Let O^k_{ijg} be the occurrence i of subgroup g under the natural hazard causing disaster impact of type j in country k for the period of 1900–2015. Such an ex ante occurrence generated disaster impact r^k_{ijg}. Define the physical loss l^k_g as the impact reported either as human fatality, people injured, people affected, or property damage in EM-DAT. We have:

$$P^k_{jg} = \sum_i O^k_{ijg} / \sum_i \sum_g O^k_{ijg} \tag{1}$$

$$l^k_{jg} = \sum_i r^k_{ijg} \tag{2}$$

The expected risk for disaster impact j for a country k, R^k_j is the sum of the products of each possible natural disaster impact times its associated probability—it is a weighted average of the various possible natural disaster impacts, with the weights being their probabilities of occurrence in country k:

$$R^k_j = \sum_g P^k_{jg} l^k_{jg} \tag{3}$$

A percentage of the expected risk for country k, E^k_j, relative to the world, can be calculated as:

$$E^k_j = R^k_j / \sum_k R^k_j \tag{4}$$

The dispersion of the expected risks are important to the understanding of disaster impacts. The tighter the dispersion, the more likely it is that the actual disaster impact will be close to the expected risk. Consequently, the less likely it is that the actual disaster loss will end up far below or above the expected loss. Thus, the less spread around the expected risk means the lower the disaster impact for a country.

The standard deviation, σ_j^k, is commonly used as the measure of the tightness of the probability distribution around the expected or mean risk. The standard deviation is a probability-weighted average deviation from the estimated impact, and it gives an idea of how far above or below a disaster impact is likely to be.

$$\sigma_j^k = [\sum_g (l_{jg}^k - R_j^k)^2 P_{jg}^k]^{1/2} \tag{5}$$

Therefore, the natural disaster risk of country k is based not only on its expected impact R_j^k in Equation (3), but also its deviation σ_j^k in Equation (5). A 95% confidence ($p < 0.05$) would provide the low-bound risk (*Low*-$R_j{}^k$) with larger of the 0 or $R_j^k - 2\sigma_j^k$ and the upper bound risk (*High*-$R_j{}^k$) with $R_j^k + 2\sigma_j^k$.

Another useful measure of expected risk is the coefficient of variation, CV_j^k which is the standard deviation divided by the expected risk. This reflects the standard deviation per unit of expected risk. It provides another meaningful basis for comparison when the disaster risks on different spaces are not the same:

$$CV_j^k = \sigma_j{}^k / R_j{}^k \tag{6}$$

The Equations (1)–(6) can be applied to all countries based on their historical impacts caused by natural disasters. Since countries vary in social-economic-physical features, it would be meaningful to see the normalized expected risks, standard deviations, and coefficients of variations by these features, such as population, gross domestic product (GDP), and land area.

$$R_{j-t}^k = R_j^k / S_t^k \tag{7}$$

$$\sigma_{j-t}^k = \sigma_j^k / S_t^k \tag{8}$$

where R_{j-t}^k and σ_{j-t}^k are normalized expected risks and standard deviations. S_t^k = social-economic features with t = population, land area, GDP, population density (PD), or per capita GDP (PG). For example, $R_{F-PD}^k = R_{Fatality}^k / S_{PD}^k$ and $\sigma_{F-PG}^k = \sigma_{Fatality}^k / S_{PG}^k$ represent the expected fatalities normalized by population density and per capita GDP, respectively. In order to have a comprehensive assessment of a nation's risk in the event of a natural disaster, the country's expected fatality, injury, people affected, and damage, as well as their standard deviations, percentages, low and upper bounds, and ranks should all be considered. In general, the larger a country's expected risk is, together with wider ranges, larger percentages, and higher ranks with expected and normalized risks, the riskier the country is expected to be.

3.2. Data Preparation

Three types of databases were used as inputs for the risk assessment model. First, the natural disaster database was obtained from EM-DAT, a global disaster database published by CRED in Brussels [8]. EM-DAT was compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes and press agencies and organized for disaster groups for natural disasters, technological disasters, and complex disasters—each of which is further split into subgroup, type, and subtype [5]. Each natural disaster contains important disaster—human injuries, fatalities, people affected, and damages—by space (e.g., continent, region, country) and time (e.g., year). Second, the world country boundary GIS (Geographic Information System) database was drawn from Global Administrative Unit Layers (GAUL) for the world developed by the Food and Agriculture Organization (FAO) of the United Nations [35]. This world boundary data was used together with the EM-DAT database for the model. Third, the world social-economic attributes of historical country population, area, and GDP data were extracted from the World Development Indicators database by the World Bank [36].

Figure 2 outlines the necessary steps for database processing. The first step is to process tables of human injuries, fatalities, people affected, and damages by country and by year for natural disasters using the EM-DAT database for the period of 1900 to 2015. The second step is to calculate probability weighted risk impacts, their standard deviations, ranks, percentages, and correlations of socio-economic attributes by country. This step also involves validation using the observed natural disaster data and the results for the model using scatter plots and Pearson correlation and Spearman rank order correlation. The third step is to perform GIS functions using "Summarize", "Join", and "Field Calculator" on the tables produced in the first and second steps, and the World Boundary GIS layer. This step also produces spatial visualizations of natural disaster risks by country.

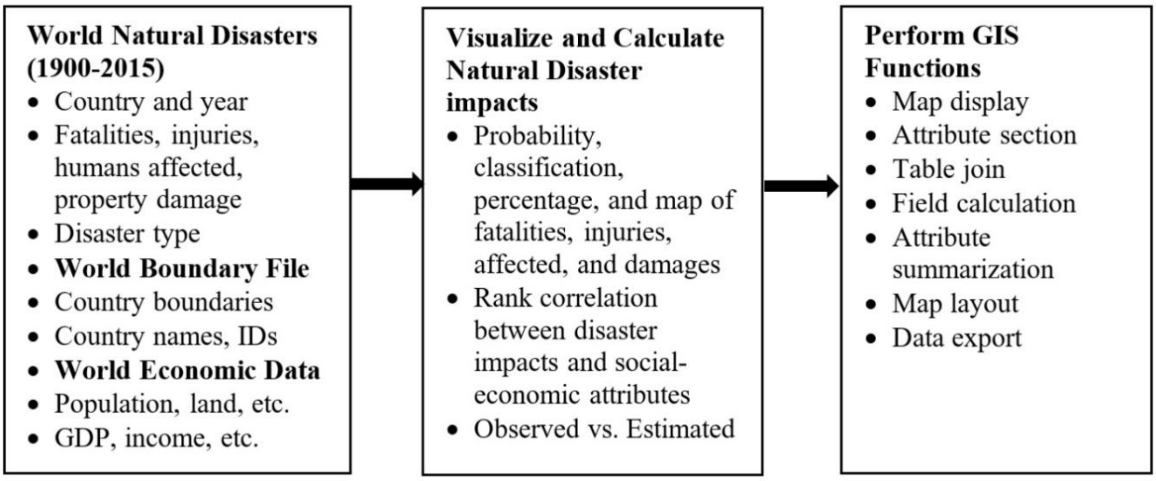

Figure 2. Modeling process and notation.

4. Results and Discussion

Expected risks and their relevant measures for ranking, dispersion, percentage, and correlation for the 208 countries selected in this study are summarized in Tables 2–5. This only lists the top 30 countries, according to expected fatality, injured, affected, and damage.

4.1. Fatality

Table 2 ranks the top 30 countries according to the expected fatality ($R^k{}_F$) and its normalized expected fatality ($R^k{}_{F\text{-}PG}$, $R^k{}_{F\text{-}PD}$). The table also lists rank ($Rank^k{}_F$), dispersion ($\sigma^k{}_I$, $Low\text{-}R^k{}_I$, $High\text{-}R^k{}_I$), coefficient of variance ($CV^k{}_F$), and total observed fatality and estimated fatality for each of the 208 countries.

Firstly, the top 30 countries in expected fatality spread over the global continents. With China, India, Bangladesh top all in Asia; Russia and Italy in Europe; Uganda, Niger, and Ethiopia sit high in Africa; and Guatemala, Peru, Chile and the United States hold the top spots in Americas. While Asia has the most countries ranked in the top 30 and had the most deaths, Oceania has no country listed. Secondly, China is particularly deadly with almost 50% of world fatalities, followed by India and Bangladesh at almost 17% and 9%, respectively. Thirdly, the dispersion measures are quite wide and large for top countries, but their spreads per unit expected fatality are quite different (e.g., smaller for China with CV = 0.86 and Uganda with CV = 0.72, but larger for India with CV = 1.76, Russia with CV = 1.56, Ethiopia with CV = 2.08, and Haiti with CV = 2.49). Finally, the ranks of expected deaths and ranks of normalized expected fatalities correspond, as do the observed and estimated total fatalities.

Table 2. Expected fatalities and relevant statistics for top 30 countries.

Country/Region	$Rank^k{}_F$	$R^k{}_F$	$\sigma^k{}_F$	$E^k{}_F$	$Low\text{-}R^k{}_F$	$High\text{-}R^k{}_F$	$CV^k{}_F$	$R^k{}_{F\text{-}PD}$	$Rank^k{}_{F\text{-}PD}$	$R^k{}_{F\text{-}PG}$	$Rank^k{}_{F\text{-}PG}$	Observed	Estimated
China	1	3,113,395	2,680,811	49.49%	0	8,475,017	0.86	22,740	2	622.7	1	12,720,326	15,566,976
India	2	1,047,303	1,838,984	16.65%	0	4,725,272	1.76	3143	4	361.1	2	9,124,242	5,236,517
Bangladesh	3	554,033	575,905	8.81%	0	1,705,843	1.04	541	17	291.6	3	2,992,580	2,770,164
Russia	4	476,958	741,707	7.58%	0	1,960,373	1.56	56,995	1	53.6	7	3,930,026	2,384,792
Uganda	5	100,770	72,455	1.60%	0	245,680	0.72	844	11	72.0	6	204,697	503,848
Indonesia	6	87,188	83,017	1.39%	0	253,223	0.95	682	12	27.2	9	241,331	435,941
Iran	7	79,754	51,134	1.27%	0	182,023	0.64	1913	5	11.4	15	156,242	398,769
Niger	8	75,676	46,397	1.20%	0	168,470	0.61	7655	3	94.6	4	194,964	378,378
Japan	9	66,685	73,507	1.06%	0	213,699	1.10	198	29	2.4	32	244,348	333,425
Ethiopia	10	63,167	131,607	1.00%	0	326,381	2.08	952	9	90.2	5	416,201	315,835
Cape Verde Is	11	47,282	28,158	0.75%	0	103,598	0.60	453	21	33.8	8	85,286	236,409
Burma	12	45,134	55,569	0.72%	0	156,271	1.23	646	15	25.1	10	146,128	225,669
Turkey	13	44,518	31,945	0.71%	0	108,407	0.72	494	19	6.6	22	92,106	222,589
Italy	14	37,511	44,907	0.60%	0	127,325	1.20	194	31	1.4	42	140,517	187,554
Pakistan	15	34,597	49,036	0.55%	0	132,669	1.42	168	33	16.5	11	174,187	172,983
Philippines	16	30,546	16,858	0.49%	0	64,262	0.55	102	40	6.6	23	69,809	152,729
Guatemala	17	27,382	22,067	0.44%	0	71,517	0.81	243	25	6.7	21	84,048	136,910
Peru	18	26,659	28,105	0.42%	0	82,869	1.05	1211	7	5.2	24	96,019	133,293
Chile	19	22,212	22,884	0.35%	0	67,980	1.03	1042	8	2.2	34	61,219	111,059
Sudan	20	21,440	43,768	0.34%	0	108,975	2.04	1303	6	11.3	16	162,688	107,198
United States	21	20,748	9276	0.33%	2195	39,300	0.45	670	14	0.5	57	43,625	103,738
Venezuela	22	19,125	9101	0.30%	923	37,327	0.48	678	13	4.0	28	31,284	95,624
Mozambique	23	15,585	32,115	0.25%	0	79,816	2.06	635	16	13.0	14	105,985	77,926
Haiti	24	12,428	30,907	0.20%	0	74,242	2.49	42	56	7.8	19	249,111	62,142
Nigeria	25	12,147	7951	0.19%	0	28,050	0.65	85	45	13.5	12	24,388	60,737
Vietnam	26	11,921	7140	0.19%	0	26,202	0.60	47	53	4.8	25	26,153	59,605
Hong Kong (China)	27	11,112	8680	0.18%	0	28,471	0.78	2	127	0.4	64	24,575	55,558
Colombia	28	10,435	9997	0.17%	0	30,428	0.96	273	24	1.7	39	33,564	52,173
Burkina Faso	29	8290	6149	0.13%	0	20,589	0.74	163	34	7.5	20	17,248	41,449
Honduras	30	8125	9442	0.13%	0	27,009	1.16	124	36	3.1	30	28,486	40,623

Note: $Rank^k{}_F$ = ranking based on expected fatality; $R^k{}_{F\text{-}PG}$ = expected fatality/per capita gross domestic product (GDP); $R^k{}_{F\text{-}PD}$ = expected fatality/population density; $Rank^k{}_{F\text{-}PG}$ = ranking for expected fatality normalized by per capita GDP; $Rank^k{}_{F\text{-}PD}$ = ranking for expected fatality normalized by population density; observed/estimated = recorded/calculated total fatalities of all natural disasters in a country.

Table 3. Expected injuries and relevant statistics for top 30 countries.

Country/Region	$Rank^k{}_I$	$R^k{}_I$	$\sigma^k{}_I$	$E^k{}_I$	$Low\text{-}R^k{}_I$	$High\text{-}R^k{}_I$	$CV^k{}_I$	$R^k{}_{I\text{-}PD}$	$Rank^k{}_{I\text{-}PD}$	$R^k{}_{I\text{-}PG}$	$Rank^k{}_{F\text{-}PG}$	Observed	Estimated
China	1	518,101	400,317	25.80%	0	1,318,735	0.77	3784	2	103.6	2	1,677,310	2,590,505
Bangladesh	2	516,754	327,202	25.73%	0	1,171,159	0.63	505	9	272.0	1	1,044,207	2,583,772
Peru	3	263,601	552,615	13.13%	0	1,368,832	2.10	11,970	1	51.7	4	2,064,125	1,318,006
Indonesia	4	188,347	114,107	9.38%	0	416,561	0.61	1473	4	58.9	3	431,603	941,737
Iran	5	90,029	59,743	4.48%	0	209,515	0.66	2160	3	12.9	7	173,400	450,147
Japan	6	48,083	59,790	2.39%	0	167,664	1.24	143	19	1.7	20	255,298	240,417
Turkey	7	47,923	34,743	2.39%	0	117,408	0.72	531	7	7.2	9	98,352	239,614
Philippines	8	44,435	32,195	2.21%	0	108,825	0.72	149	17	9.7	8	209,289	222,176
Pakistan	9	29,934	50,336	1.49%	0	130,606	1.68	145	18	14.3	5	159,919	149,670
Chile	10	28,152	29,362	1.40%	0	86,877	1.04	1321	5	2.8	16	77,400	140,761
Guatemala	11	26,052	29,807	1.30%	0	85,665	1.14	231	14	6.4	10	78,486	130,259
Haiti	12	21,177	70,858	1.05%	0	162,893	3.35	71	28	13.2	6	582,590	105,884
India	13	18,322	46,370	0.91%	0	111,062	2.53	55	30	6.3	11	244,895	91,612
El Salvador	14	11,340	12,605	0.56%	0	36,550	1.11	35	36	2.4	18	47,304	56,701
United States	15	9436	4869	0.47%	0	19,174	0.52	305	13	0.2	50	27,847	47,181
Brazil	16	9010	3350	0.45%	2309	15,711	0.37	408	12	1.2	23	15,100	45,050
Colombia	17	8384	6653	0.42%	0	21,690	0.79	219	15	1.3	21	24,118	41,921
Sudan	18	7669	7275	0.38%	0	22,219	0.95	466	10	4.0	14	19,216	38,347
Russia	19	6969	6929	0.35%	0	20,828	0.99	833	6	0.8	31	29,437	34,846
Mexico	20	6818	11,707	0.34%	0	30,232	1.72	125	20	0.8	32	36,684	34,088
Macedonia FRY	21	6812	6075	0.34%	0	18,962	0.89	84	26	1.0	25	20,062	34,058
Vietnam	22	6627	4356	0.33%	0	15,339	0.66	26	42	2.7	17	13,702	33,134
Burma	23	6377	7791	0.32%	0	21,959	1.22	91	24	3.5	15	20,762	31,887
Algeria	24	5711	7608	0.28%	0	20,928	1.33	413	11	1.0	26	21,615	28,557
Dominican Rep	25	4988	4094	0.25%	0	13,176	0.82	26	41	0.8	29	11,316	24,940
Nicaragua	26	4391	7496	0.22%	0	19,384	1.71	102	22	1.9	19	21,467	21,957
Taiwan (China)	27	4022	4176	0.20%	0	12,373	1.04	6	70	0.2	56	20,404	20,109
Italy	28	3858	4916	0.19%	0	13,689	1.27	20	51	0.1	61	13,428	19,288
Honduras	29	3263	4565	0.16%	0	12,393	1.40	50	32	1.3	22	12,217	16,313
Madagascar	30	3237	1042	0.16%	1153	5322	0.32	102	21	4.0	13	5050	16,186

Note: $Rank^k{}_I$ = ranking based on expected injuries; $R^k{}_{I\text{-}PG}$ = expected injuries/per capita GDP, $R^k{}_{I\text{-}PD}$ = expected injuries/population density; $Rank^k{}_{I\text{-}PG}$ = ranking for expected injuries normalized by per capita GDP; $Rank^k{}_{I\text{-}PD}$ = ranking for expected injuries normalized by population density; observed/estimated = recorded/calculated total injuries of all natural disasters in a country.

Table 4. Expected people affected and relevant statistics for top 30 countries.

Country/Region	$Rank^k{}_A$	$R^k{}_A$	$\sigma^k{}_A$	$E^k{}_A$	$Low\text{-}R^k{}_A$	$High\text{-}R^k{}_A$	$CV^k{}_A$	$R^k{}_{A\text{-}PD}$	$Rank^k{}_{A\text{-}PD}$	$R^k{}_{A\text{-}PG}$	$Rank^k{}_{A\text{-}PG}$	Observed	Estimated
India	1	429,191,905	303,911,868	32.11%	0	1,037,015,641	0.71	1,288,177	3	147,997	1	1,066,532	2,145,960
China	2	286,388,736	245,383,239	21.43%	0	777,155,213	0.86	2,091,717	1	57,278	3	1,321,453	1,431,944
Bangladesh	3	130,170,085	123,868,560	9.74%	0	377,907,205	0.95	127,197	32	68,511	2	423,956	650,850
Philippines	4	89,426,690	48,834,676	6.69%	0	187,096,043	0.55	299,859	14	19,441	5	186,737	447,133
Pakistan	5	43,274,103	25,104,141	3.24%	0	93,482,385	0.58	209,825	22	20,607	4	86,670	216,371
Vietnam	6	36,607,540	20,594,716	2.74%	0	77,796,971	0.56	142,938	30	14,643	7	84,807	183,038
Thailand	7	35,345,770	19,738,520	2.64%	0	74,822,810	0.56	281,097	15	4776	16	90,770	176,729
Brazil	8	22,774,074	16,452,819	1.70%	0	55,679,712	0.72	1,030,699	4	2997	22	73,371	113,870
United States	9	11,289,909	5,981,071	0.84%	0	23,252,052	0.53	364,349	11	299	65	27,612	56,450
Ethiopia	10	11,065,843	21,900,304	0.83%	0	54,866,452	1.98	166,795	27	15,808	6	69,587	55,329
Colombia	11	10,592,747	4,124,418	0.83%	2,343,911	18,841,584	0.39	276,746	16	1681	31	16,970	52,964
Sri Lanka	12	10,381,781	4,355,256	0.83%	1,671,270	19,092,292	0.42	33,683	54	2806	24	25,199	51,909
Kenya	13	10,056,923	15,231,044	0.83%	0	40,519,011	1.51	168,828	26	10,057	8	57,054	50,285
Indonesia	14	9,015,883	5,540,515	0.83%	0	20,096,914	0.61	70,504	39	2817	23	28,803	45,079
Korea (North)	15	8,363,335	3,476,049	0.83%	1,411,237	15,315,432	0.42	43,617	47	6433	11	16,074	41,817
Argentina	16	7,656,822	4,802,257	0.83%	0	17,261,337	0.63	530,677	7	684	48	14,745	38,284
Cambodia	17	7,462,102	4,992,182	0.83%	0	17,446,467	0.67	97,320	37	3927	17	19,891	37,311
Madagascar	18	7,244,752	2,430,940	0.83%	2,382,872	12,106,632	0.34	228,709	20	9056	9	13,271	36,224
Cuba	19	6,709,627	4,048,723	0.83%	0	14,807,073	0.60	65,347	41	2314	26	13,745	33,548
Mozambique	20	6,486,178	6,858,975	0.83%	0	20,204,128	1.06	264,103	17	5405	14	31,100	32,431
Sudan	21	6,360,185	9,367,367	0.83%	0	25,094,919	1.47	386,489	10	3347	19	38,508	31,801
Japan	22	6,056,199	3,977,189	0.83%	0	14,010,577	0.66	17,952	70	215	71	18,864	30,281
Mexico	23	5,554,300	3,915,270	0.83%	0	13,384,840	0.70	101,965	36	617	51	18,766	27,771
Peru	24	4,922,971	3,551,513	0.83%	0	12,025,997	0.72	223,552	21	965	45	18,743	24,615
Australia	25	4,558,311	4,563,992	0.83%	0	13,686,296	1.00	1,729,121	2	157	82	16,137	22,792
Niger	26	4,519,191	8,097,829	0.83%	0	20,714,848	1.79	457,147	9	5649	13	25,377	22,596
Nigeria	27	4,474,124	3,906,089	0.83%	0	12,286,302	0.87	31,344	57	4971	15	13,534	22,371
Russia	28	4,105,732	5,043,289	0.83%	0	14,192,310	1.23	490,618	8	461	57	30,087	20,529
Chile	29	3,963,895	3,622,404	0.83%	0	11,208,703	0.91	185,969	23	400	59	11,561	19,819
Turkey	30	3,942,522	2,532,515	0.83%	0	9,007,552	0.64	43,705	46	588	52	8847	19,713

Note: $Rank^k{}_A$ = ranking based on expected people affected; $R^k{}_{A\text{-}PG}$ = expected people affected/per capita GDP, $R^k{}_{A\text{-}PD}$ = expected people affected/population density; $Rank^k{}_{A\text{-}PG}$ = ranking for people affected normalized by per capita GDP; $Rank^k{}_{A\text{-}PD}$ = ranking for people affected normalized by population density; observed/estimated = recorded/calculated total affected of all natural disasters in a country.

Table 5. Expected damage and relevant statistics for top 30 countries.

Country/Region	$Rank^k{}_D$	$R^k{}_D$	$\sigma^k{}_D$	$E^k{}_D$	$Low\text{-}R^k{}_D$	$High\text{-}R^k{}_D$	$CV^k{}_D$	$R^k{}_{D\text{-}PD}$	$Rank^k{}_{D\text{-}PD}$	$R^k{}_{D\text{-}PG}$	$Rank^k{}_{D\text{-}PG}$	Observed	Estimated
United States	1	387,858,549	174,002,830	37.63%	39,852,888	735,864,210	0.45	12,517,008	1	10,261	2	755,581	1,939,293
China	2	125,100,675	90,084,817	12.14%	0	305,270,310	0.72	913,706	5	25,020	1	419,431	625,503
Japan	3	116,493,701	135,054,963	11.30%	0	386,603,626	1.16	345,317	9	4131	6	429,770	582,469
Italy	4	26,420,875	21,295,576	2.56%	0	69,012,028	0.81	136,905	19	990	20	86,385	132,104
Thailand	5	26,285,526	14,682,585	2.55%	0	55,650,696	0.56	209,043	16	3552	7	47,716	131,428
Germany	6	23,262,180	13,908,240	2.26%	0	51,078,660	0.60	100,763	24	843	22	58,091	116,311
India	7	21,437,918	14,447,192	2.08%	0	50,332,303	0.67	64,344	30	7392	4	57,994	107,190
Australia	8	14,596,461	9,458,874	1.42%	0	33,514,209	0.65	5,536,930	2	503	30	45,064	72,982
France	9	13,993,522	10,414,923	1.36%	0	34,823,367	0.74	125,745	21	507	28	39,637	69,968
Mexico	10	13,574,913	11,048,321	1.32%	0	35,671,555	0.81	249,207	12	1508	16	41,090	67,875
United Kingdom	11	13,457,758	8,857,592	1.31%	0	31,172,942	0.66	54,360	34	486	31	32,816	67,289
Chile	12	13,341,040	13,347,342	1.29%	0	40,035,723	1.00	625,906	6	1348	17	37,627	66,705
Korea (North)	13	12,924,814	5,371,395	1.25%	2,182,023	23,667,604	0.42	67,406	29	9942	3	23,653	64,624
Turkey	14	12,828,689	8,850,369	1.24%	0	30,529,427	0.69	142,214	18	1915	14	26,910	64,143
Pakistan	15	11,630,543	6,580,797	1.13%	0	24,792,138	0.57	56,394	33	5538	5	26,278	58,153
Philippines	16	11,387,888	6,219,309	1.10%	0	23,826,507	0.55	38,185	39	2476	10	22,984	56,939
Iran	17	9,141,422	5,037,113	0.89%	0	19,215,648	0.55	219,325	15	1306	18	22,765	45,707
Spain	18	8,964,725	6,924,680	0.87%	0	22,814,085	0.77	112,017	22	407	37	28,395	44,824
Russia	19	8,066,475	7,311,598	0.78%	0	22,689,670	0.91	963,911	4	906	21	31,860	40,332
Brazil	20	7,856,861	4,389,833	0.76%	0	16,636,527	0.56	355,582	8	1034	19	21,178	39,284
Indonesia	21	7,856,128	5,443,985	0.76%	0	18,744,098	0.69	61,435	31	2455	11	27,663	39,281
Canada	22	7,679,467	6,341,308	0.75%	0	20,362,084	0.83	2,316,599	3	258	48	27,712	38,397
Korea (South)	23	7,598,414	4,762,590	0.74%	0	17,123,595	0.63	15,319	59	427	36	16,067	37,992
Bangladesh	24	6,251,796	4,976,261	0.61%	0	16,204,318	0.80	6109	80	3290	8	18,191	31,259
Taiwan (China)	25	6,186,056	4,957,850	0.60%	0	16,101,757	0.80	9662	67	264	47	20,884	30,930
Cuba	26	6,084,845	3,837,252	0.59%	0	13,759,350	0.63	59,262	32	2098	12	11,642	30,424
Argentina	27	5,426,051	3,402,172	0.53%	0	12,230,394	0.63	376,067	7	484	32	10,398	27,130
Oman	28	4,951,000	0	0.48%	4,951,000	4,951,000	0.00	339,075	10	378	41	4951	24,755
Vietnam	29	4,649,464	2,627,027	0.45%	0	9,903,517	0.57	18,154	55	1860	15	10,615	23,247
New Zealand	30	4,588,068	8,515,566	0.45%	0	21,619,201	1.86	302,424	11	212	53	26,443	22,940

Note: $Rank^k{}_D$ = ranking based on expected damage; $R^k{}_{D\text{-}PG}$ = expected damage/per capita GDP, $R^k{}_{D\text{-}PD}$ = expected damage/population density; $Rank^k{}_{D\text{-}PG}$ = ranking for expected damage normalized by per capita GDP; $Rank^k{}_{D\text{-}PD}$ = ranking for expected damage normalized by population density; observed/estimated = recorded/calculated total damage of all natural disasters in a country, in \$1000.

4.2. Injured

Similar to the results of expected fatalities discussed just above, Table 3 ranks the top 30 countries according to their expected injuries ($R^k{}_I$) and their normalized expected injuries ($R^k{}_{I\text{-}PG}$, $R^k{}_{I\text{-}PD}$). The table also lists rank ($Rank^k{}_I$), dispersion ($\sigma^k{}_I$, $Low\text{-}R^k{}_I$, $High\text{-}R^k{}_I$), coefficient of variance ($CV^k{}_I$), and total observed and estimated injuries.

Firstly, top 30 countries in expected injuries are found in all continents, with China, Bangladesh, and Indonesia leading in Asia; Russia, Macedonia, and Italy in Europe; Sudan and Algeria in Africa; Peru, Guatemala, Haiti, El Salvador; and the United States in Americas. Again, Asia has the most countries ranked in the top 30 and the most deaths, while Oceania has no country listed. Secondly, China and Bangladesh are particularly vulnerable to injuries, with each having over 25% of the world total, followed by Peru, Indonesia, and Iran with 13.13%, 9.38%, and 4.48%, respectively. Thirdly, the dispersion measures are quite wide and large for top 30 countries, but their spreads per unit expected injuries are quite different (e.g., small for China with CV = 0.77 and Bangladesh with CV = 0.63, but large for Peru with CV = 2.10, Haiti with CV = 3.35, and India with CV = 2.53). Finally, the ranks of expected injuries and ranks of normalized expected injuries are quite similar, as are the total observed and estimated injuries.

4.3. Affected

Table 4 shows the top 30 countries in which people were affected by natural disasters. There are several numbers worth noting in this table. Firstly, Asian countries are expected to produce the highest expected number of people affected in the event of a disaster, For example, India had the number of people affected with more than 429 million (or 32.11%), followed by China with over 286 million (or 21.43%). These countries, alongside Bangladesh (9.74%), Philippines (6.69%), and Pakistan (3.24%) make up the top 5. The top 30 rankings also included: Brazil, the United States, Colombia, Argentina, Cuba, Mexico, Peru, and Chile in Americas; and Ethiopia, Kenya, Mozambique, Madagascar, Sudan, Niger, and Nigeria in Africa. Secondly, Australia is the only country from Oceania; as is Russia from Europe, in the top 30. Thirdly, again, Asia is the top continent with 11 countries, including the top 7, in the top 30. Fourthly, the dispersion measures are relatively significant, but the standard deviation per unit of expected people affected are relatively small, especially the top 10 with CV = 0.53 for the United States and CV = 0.86 for China, except for Ethiopia with CV = 1.98. Finally, the ranks for expected people affected normalized by population density and per capita GDP are very similar, so are the observed and estimated total people affected.

These results show that casualties, injuries, and people affected by natural disasters are highly correlated to population size, distribution, and density in general [17], and perhaps more to vulnerable population groups in particular [37].

4.4. Damage

Table 5 provides the top 30 countries which suffered severe physical damage by natural disasters. The damages were measured by monetary value, in $1000 U.S. dollars. It should be noted that the United States, which was ranked 21st in expected fatalities; 15th in expected injuries, 9th in people affected, received the highest ranking with 37.63% of the world expected damages, followed by Mexico, Chile, Brazil, Canada, Cuba and Argentina in Americas. In addition, some new faces from developed countries—for example: Italy, Germany, France, United Kingdom in Europe; and Australia and New Zealand in Oceania—also appeared in the top 30 countries. Many Asian countries, such as China, Japan, China (12.14%), Japan (11.30%), Thailand, India, Koreas, were in the top 30. The ranges are higher for the top countries, while the dispersions of per unit expected damage are fairly small (e.g., the United States with CV = 0.45), except New Zealand with CV = 1.86 and Japan with CV = 1.16. Finally, the ranks for the expected damages and the normalized expected damages quite match in values, so do the magnitudes for the total observed and estimated damages.

Properties are used by people for social, cultural, and economic activities. Therefore, property damages are presumably highly correlated with population size, distribution, and density. While many countries with high fatalities and injuries are also high in property damages, Table 5 shows this is not always the case. For example, the United States ranks quite differently in the categories of fatality, injury, and in property damage, as do some other developed nations. This observation is partially related to property damage valuation parities, or metrological differences [38].

4.5. Model Performance

The similar ranks between the expected risks and the normalized expected risks and the similar and values between the total observed and estimated risks indicate that the model performs reasonably well. We used two methods to evaluate the model's performance: the Spearman rank correlation, and the Pearson correlation. Both are shown in scatter plots, with correlation and R and R^2 values, in Figure 3. The Spearman rank correlations were calculated for $Rank^k{}_j$ vs. $Rank^k{}_{j\text{-}PG}$, $Rank^k{}_{j\text{-}PD}$. Whereas, the Pearson correlations were computed for estimated and observed totals for fatality, injured, affected, and damage. It is believed that the higher the R and R^2 values, the better the correlations, and the better the model's performance.

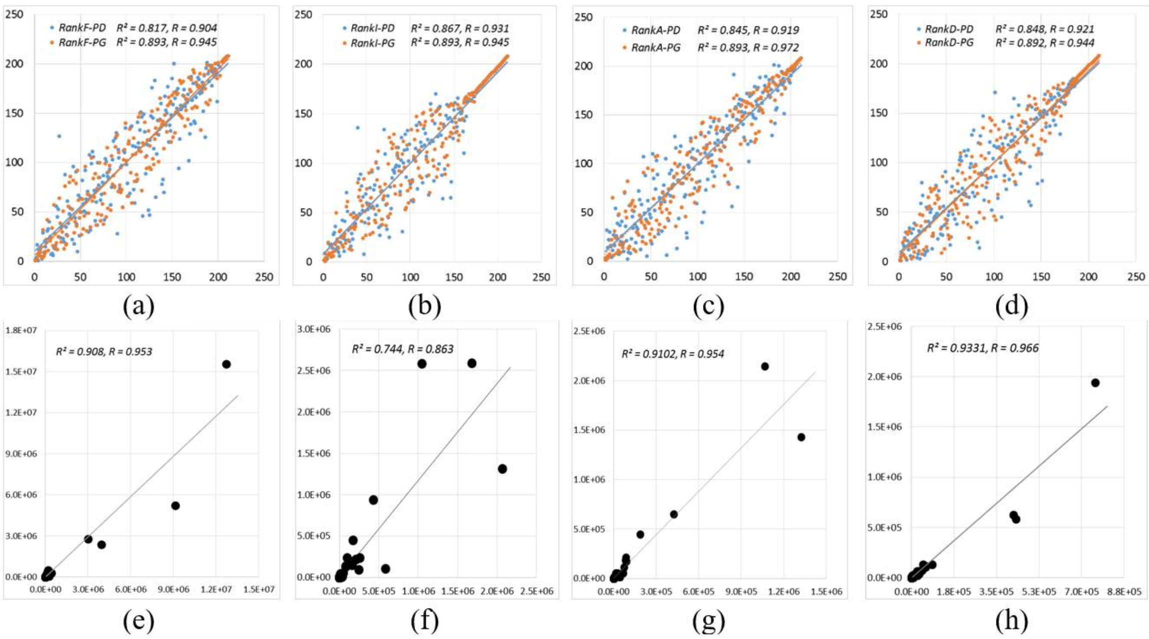

Figure 3. Scatter plots with Pearson and Spearman rank correlation values. (**a**) the Spearman rank correlation between the total observed and estimated fatality risk; (**b**) the Spearman rank correlation between the total observed and estimated injure risk; (**c**) the Spearman rank correlation between the total observed and estimated affected risk; (**d**) the Spearman rank correlation between the total observed and estimated damage risk; (**e**) the Pearson correlation between the total observed and estimated fatality risk; (**f**) the Pearson correlation between the total observed and estimated injure risk; (**g**) the Pearson correlation between the total observed and estimated affected risk; (**h**) the Pearson correlation between the total observed and estimated damage risk.

Shown in Figure 3, the Spearman rank correlations for the expected risks and normalized expected risks are very high, ranging from the low 0.904 for fatality (a) $Rank^k{}_F$ vs. $Rank^k{}_{F\text{-}PD}$ to the high 0.972 for affected (c) $Rank^k{}_A$ vs. $Rank^k{}_{A\text{-}PG}$. The Pearson correlations are also very high, ranging from the low 0.863 for affected (g) to the high 0.966 for damage (h). It is interesting to note that from Figure 3 (a–d) the lower or higher ranked countries in particular have much higher correlations. This is especially true, due to the small but similar expected and normalized expected risks for countries ranked after 150 for injured (b), and after 175 for damaged (d).

The scatter plots Figure 3 (e–h) show all observed and estimated data points, including top ranked countries with extremely large total risks. These top hotspots may be statistically regarded as outliers or influential points, but they are not removed due to their apparent importance for global risk analysis, especially for ranking.

4.6. Natural Disaster Hot-Spots

Table 6 summarizes the percentage shares of the expected and normalized expected fatality, injured, affected, and damage by the top 10, 20, and 30 countries, and then the remaining 178 countries. Their percentage shares of total estimated and observed disaster impacts are also shown in Table 6. The top 10, 20, and 30 countries respectively accounted for more than 90%, 95%, and 97% for expected fatality ($R^k{}_F$); 88%, 94%, and 97% for expected injury ($R^k{}_I$); 81%, 88%, and 91% for expected people affected; and 74%, 85%, and 91% for expected damage. Meaning that if historical trends and patterns continue, more than 91% of losses from future natural disasters are expected to happen in those 30 nations, especially those in the top 10. The remaining 178 countries only shared 2.52%, 2.92%, 8.13%, and 8.82% of the expected risks, implying quite a few countries, especially smaller ones, did not experience many natural disasters.

Table 6. Shares of natural disaster impacts of the top 10, 20, and 30 countries.

Subgroup	Country	$R^k{}_j$	$\sigma^k{}_j$	$R^k{}_{j\text{-}PD}$	$R^k{}_{j\text{-}PG}$	*Observed*	*Estimated*
Fatality	Top 10	90.06%	91.01%	86.87%	86.45%	92.92%	90.06%
	Top 20	95.42%	95.97%	92.19%	92.58%	96.34%	95.42%
	Top 30	97.48%	97.86%	94.66%	95.57%	98.13%	97.48%
	Remaining 178	2.52%	2.14%	5.34%	4.43%	1.87%	2.52%
Injured	Top 10	88.40%	83.82%	80.09%	88.04%	80.12%	88.40%
	Top 20	94.63%	93.94%	90.00%	94.06%	94.43%	94.63%
	Top 30	97.08%	96.57%	93.33%	96.78%	96.50%	97.08%
	Remaining 178	2.92%	3.43%	6.67%	3.22%	3.50%	2.92%
Affected	Top 10	81.96%	79.22%	36.56%	73.50%	79.51%	81.96%
	Top 20	88.24%	84.54%	47.40%	82.92%	85.00%	88.24%
	Top 30	91.87%	89.17%	69.74%	86.55%	89.64%	91.87%
	Remaining 178	8.13%	10.83%	30.26%	13.45%	10.36%	8.13%
Damage	Top 10	74.61%	74.29%	70.80%	49.48%	74.77%	74.61%
	Top 20	85.24%	85.24%	80.04%	72.41%	85.13%	85.24%
	Top 30	91.18%	91.99%	92.32%	83.02%	91.72%	91.18%
	Remaining 178	8.82%	8.01%	7.68%	16.98%	8.28%	8.82%

The similar patterns can be found in percentage shares of expected risks normalized by: Population density and per capita GDP, total observed and estimated risks, and the risk dispersion ($\sigma^k{}_j$). Referencing to the specific top 30 countries in Tables 3–6, we can say that the natural disaster hotspots are mostly in Asia (e.g., China, India, Bangladesh), a few in North America (e.g., the United States), some in Europe (e.g., Russia, Italy, Germany), and Africa (e.g., Ethiopia, Sudan, Niger, Algeria). While Oceania and small countries are relatively safe places for natural disasters.

Figure 4 illustrates the spatial distribution of expected disaster risks at the country-level. The countries, which have a higher number of expected fatalities, injuries, people affected and damages, are represented in darker brown colors.

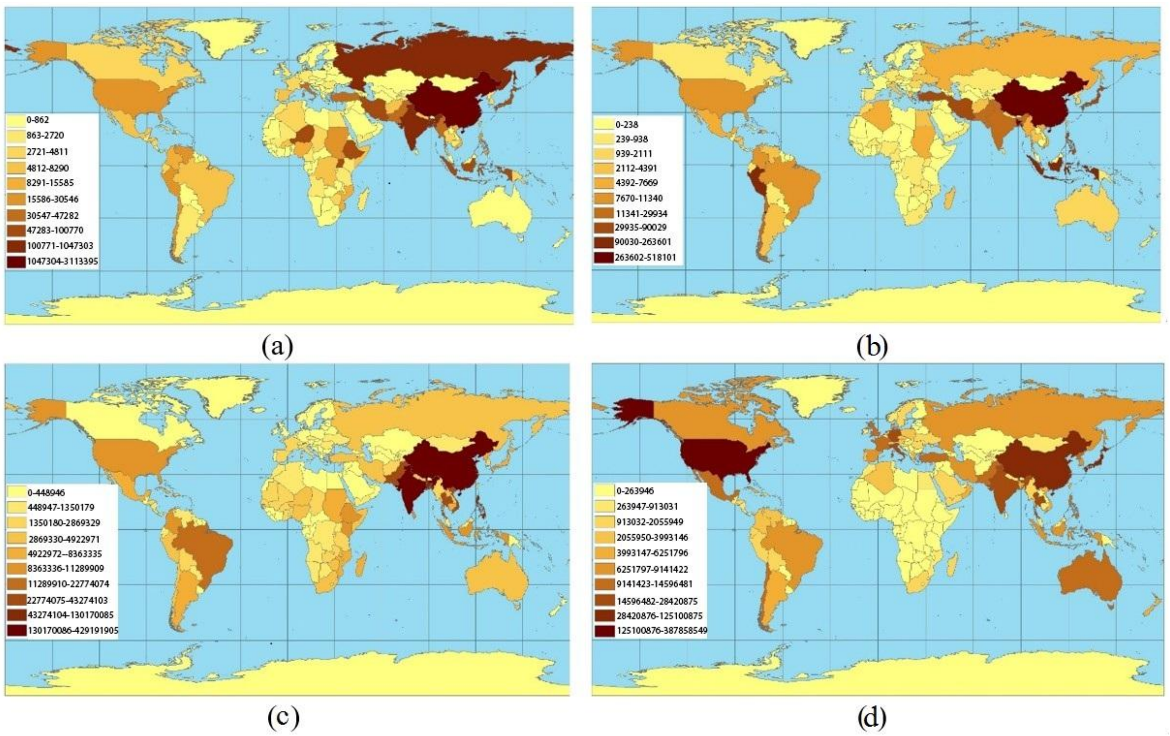

Figure 4. Spatial distribution of expected natural disaster impacts by country. (**a**) the spatial distribution of the expected disaster risk of fatalities; (**b**) the spatial distribution of the expected disaster risk of injuries; (**c**) the spatial distribution of the expected disaster risk of people affected; (**d**) the spatial distribution of the expected disaster risk of damages.

5. Conclusions and Remarks

A natural hazard (such as floods, earthquakes, and hurricanes) is an event that happens in 'mother nature'. However, a natural disaster causing deaths, injuries, and property losses occurs through interactions between natural and the man-made environments. No country can be immune from natural hazards. However, some countries are suffered more from natural disasters than others. One of the major findings of this research is that natural disasters occurred during the period of 1900 to 2015 severely impacted human lives and economies of countries—especially the top 10, 20, and 30 countries ranked by expected risks. These top hot spots are also large, populated, developed, or rapidly developing ones. For example, the United States received the highest ranking in terms of natural disaster occurrence. This was followed by China, India, the Philippines, Indonesia, Bangladesh, and Japan—all of which are located in Asia. The nations suffering the most from fatalities were China, India, Russia, Bangladesh, and Ethiopia; while the highest number of injuries happened in Peru, China, Bangladesh, Haiti, Indonesia, Japan, and India. Also, the United States was ranked first in terms of damage, which was followed by Japan, China, Italy and Germany. All of these nations with high damages also had high gross domestic products. These results indicate that natural disasters happened in nations across every continent (e.g., Asia, Europe, Africa, and America), even though some countries experienced more losses than others. These findings support the research by Dilley [25], and Giuliani and Peduzzi [23]. Perhaps more important is the high correlations between the expected risk and the socio-economically normalized expected risks: Indicating not only the relevance of the population density and per capita GDP for risk analyses, but the success of this model's performance.

The model calculates expected human fatalities, injures, people affected, and economic damages along with their relevant percentages, ranges, and ranks, for 208 countries in the world. Scatter plots and Spearman rank correlations between expected risks and normalized expected risks indicate that the model perform well. In addition, the scatter plots and Pearson correlations showed that the total estimated human casualties and economic losses aligned with the corresponding observed disaster totals. For example, China, ranked first in terms of the 'real' number of fatalities from natural disasters, and also held the first position in 'expected' risk of fatalities. Similarly, India and Bangladesh, which were the second and fourth nations in terms of the 'real' fatalities, and took the second and third rankings, respectively, in the total estimated fatalities. Furthermore, the United States, Japan, and China, which had the first, second, and third rankings in the total observed economic damages, respectively, were ranked first, third, and second in the total estimated economic damages. The results and rankings from this model are synthetic in nature and similar to Munich [39] on natural hazard index, and Dilley [25] on natural disaster hotspot analysis, hence, cross-model comparative studies may be warranted.

Finally, the expected risk model, based upon the widely used EM-DAT historical natural disaster data, can be used as a new alternative approach to conduct country-level risk assessments—or risk analyses of fatality, injured, affected, and damage, especially for counties' governments to make sound disaster preparation and mitigation decisions, policies, or plans regarding natural disasters. Local governments at the state, provincial, or municipal levels in a country can also use the model, if disaster datasets for jurisdiction-specific natural disaster information is available. The model can also be tested for specific natural disasters, especially floods, earthquakes, and hurricanes, so that more specific prevention, evaluation, mitigation, and recovery policies or plans can be made and implemented to minimize risks or losses from natural disasters. However, the reliability and validity of EM-DATA are critical for all these efforts. Therefore, cross-database comparative studies, especially for databases with similar spatial and temporal coverages as used in Giuliani and Peduzzi [20], and Gregorowski et al. [40], are also imperative.

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