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Development of Damage Prediction Formula for Natural Disasters Considering Economic Indicators

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Abstract: Damage caused by natural disasters produces the difference of damage size not only according to damage volume or size, but a national economic level. In addition, budgets and aids should be constantly acquired for disaster management since natural disasters sporadically or irregularly occur. This study proposed disaster management methods by countries considering natural disaster damage documents and economic indicators from 1900 to 2017 among 187 countries in the world. It developed a damage prediction formula considering damage documents of previous natural disasters, economic indicators by countries, and basic indicators as disaster management methods by countries. Independent variables of the damage prediction formula include GDP, population, and area. It applied multiple regression analysis and calculated average human losses due to death, human losses affected, and damage costs by countries. Regarding the adjusted R^2 of the natural disaster damage prediction formula, the human losses from deaths mean was 0.893, the human losses affected mean was 0.915, and the damage costs mean was 0.946, which had higher explanatory powers. Therefore, results from this study are considered to calculate quantitative damage sizes considering uncertain damage sizes of natural disasters, economic indicators by countries, and are used as indicators for disaster management.

Keywords: natural disaster; damage prediction; economic indicators; human losses; damage costs

1. Introduction

Natural disasters sweeping the world are unpredictable in terms of damage size and damage scope. Studies are conducted to predict natural disasters and prepare for them in many different countries. Natural disasters are events that repeatedly cause damage and economic loss in various fields. Natural disasters have long been an area of great interest in the international community. Despite various studies and disaster reduction, the frequency and size of disasters continues to increase. Although the effects of natural disasters on humans are extensive, economic development for human convenience makes the damage worse [1].

Abnormal climates frequently occur due to effects from the recent climate change and national development projects, which increases the possibility of occurring disasters and massive damages [2–5]. For this reason, a variety of research on disaster management is conducted in many countries to improve the ability to predict and prepare for natural disasters. In addition, plenty of research has been done on natural disasters and economic impacts, but natural disasters and economic impacts are estimated to have positive or negative impacts [6]. Various prior studies on natural disasters and economic indicators are presented in detail in Chapter 2.

This study aims to develop a natural disaster damage prediction formula considering national disaster damage data, economic indicators, and basic indicators by countries in the world. Human losses from deaths, human losses affected, and damage costs were selected as natural disaster damage data. GDP, population, and area were selected as economic indicators and basic indicators by countries.

For natural disaster damage data, it calculated annual average costs by countries and the 2017 standard aimed to be applied for economic indicators and basic indicators by countries. The appropriateness of medium variables will analyze the significance through correlation analysis and a damage prediction formula will be proposed through multiple regression analysis.

2. Literature Review

The damage size of natural disasters is produced by considering various effects of not just types and sizes of disasters, but national social and economic factors. Recent studies related with disasters are performed to estimate damage sizes by using various medium variables such as previous damage data, economic indicators by countries, and basic indicators on disasters including heavy rain, earthquake, and hurricane [7–13].

We have developed a formula for economic development and natural disasters in 151 countries for about 40 years against human losses due to deaths and damage/GDP due to natural disasters. The parameters include GDP, total schooling years, size of government, openness, and M3/GDP. The analytical conditions developed a formula for human losses deaths and damage/GDP for 151 countries, OECD countries, and developing countries. The correlation of R2 was 0.09 to 0.35. The correlation coefficient between GDP and various parameters of the formula was less than $\pm$ 1 % to 2% [14]. In addition, the economic parameters are similar, but the relationship between the economic situation and economic impacts in 1985, 1995, and 2005 was analyzed for 73 countries. Death, human losses affected, and damage/GDP from natural disasters were calculated. R2 is 0.02 to 0.40 but there is a significant relationship between economic effects and natural disaster damage [15]. A formula was proposed to calculate the damage caused by natural disasters and economic development in each country. However, there was not much difference in the application of the various economic parameters in each country and the result of applying only GDP. In addition, high correlation was not analyzed in national economic development by year. Thus, it is believed that the development of the damage prediction formula for natural disasters could be developed in a simpler way if only GDP is taken into account rather than the application of various parameters.

Natural disaster damage tended to decrease as educational level and economic size increased. In addition, population and economic growth were presented, as significant factors of rising damage on natural disasters. Non-linear U-shaped correlation was analyzed on national development and disaster damage [16–19]. The government proposed that information and education should be conducted not only for the physical equipment to reduce natural disasters but also for the collective action of citizens. We analyzed the degree of exposure due to various natural disasters and the loss relation to the economic development stage by country. Countries with low or moderate risk of natural disasters have reduced economic losses and wealth, while higher countries have an increasing impact [20,21]. The study on natural disaster and national economic indicators proposed the association between natural disaster damage and economic indicators, but did not calculate quantitative damage size for managing disasters in countries. In addition, the analysis of the natural disaster risks and economic indicators, according to the level of economic development in each country, has not been developed.

The occurrence of natural disasters affects national economic growth, population, and GDP for short and long periods. Disaster size and national competitiveness were highly correlated with damage restoration power [22–26]. Although agriculture is badly affected by flood in the middle part of the United States, employment was less influenced. Even if hurricanes and storms swept big cities in the Texas Gulf Coast, the population and GDP increased. It was analyzed that natural disasters facilitated the economy for a short period in Vietnam [27–30]. We have developed multiple regression formulas for the mortality rates of human as well as architectural, social, natural, and capital resources in the coastal areas due to hurricanes. The analysis found that the death rate was significantly affected by the hurricane frequency and the negative effects of the ecological economy and GDP. However, in developing countries in Central America and the Caribbean, hurricanes have fallen by 0.84% as along with life, monetary damage, and macroeconomic growth by country [31]. Although studies on the long and short-term effects on national population, economy, and development according to damage size of national disasters were conducted, there is little research on predicting natural disaster damage and proper disaster management response and preparation methods. Although the proposed reduction of natural disasters is caused by economic development by country, it is not only a result of hurricanes but also a result of various natural disasters.

We developed an analytical formula for predicting the damage to natural disasters, according to the level of economic development. Economic development reduces human damage and losses, but causes higher losses in higher-income countries [32]. However, in large-scale natural disasters, there is no mitigation effect due to economic growth in each country [6]. Without national economic development, it was analyzed that the death toll in natural disasters increased by 20%. Therefore, it was proposed that international relief for developing countries should be promoted [33]. Regression analysis has been performed to estimate the damage from typhoons, heavy rain, hurricanes, and earthquakes by considering effects such as society, economy, and climate arisen from natural disasters. A damage prediction function was proposed by using regression analysis and the constant number law through medium variables including hurricane atmospheric pressure, wind speed, and size [8,34–38]. In addition, it analyzed the correlation through a linear relationship on the climate variable and the economic variable on various natural disasters and estimated a damage costs formula by conducting regression analysis [39–42]. The impact of natural disasters on economic development depends on the state of development of the country. We intend to develop a prediction formula for natural disasters that can take into account both economic indicators and basic indicators by 151 countries. Although the damage formula and the prediction function of various types of disasters were proposed, no research on considering a comprehensive natural disaster and a damage prediction formula to be applied in various countries has been carried out.

3. Methods

3.1. Multiple Regression Analysis

Regression analysis can be classified into simple regression analysis and multiple regression analysis, according to the distribution of variables. As shown in Formula (1), simple regression analysis means that a single dependent variable and a single independent variable assume a straight-line relationship of the first function regarding the relationship between both variables.

$$\mathrm{Y} = \beta_0 + \beta_1 X \tag{1}$$

X in this case, refers to an independent variable. Y refers to a dependent variable and β means a regression coefficient.

Multiple regression analysis is a method for estimating and predicting characteristics or the trend of population elicited by analyzing collected data. The main purpose is to estimate a value of the dependent variable when designating the value of the independent variable. Multiple regression analysis shows the straight-line relationship of the first function between more than two independent variables and a dependent variable, as shown in Formula (2).

$$\mathrm{Y} = \beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + +\beta_i \mathrm{X}_i + \varepsilon \tag{2}$$

X herein, refers to the independent variable and Y is the dependent variable. ε is the constant number and $\beta_0, \beta_1, \beta_2, \ldots, \beta_i$ are regression coefficients.

It is important to review the validity of estimated multiple regression analysis and representation and accuracy on the given data. R^2, which is a coefficient of determination and VIF, and is a variance inflation factor, are applied as a method to specify the degree of multiple regression analysis among various specification methods. The coefficient of determination is SST (Total Sum of Squares) and SSE ratio, which is the sum of SSE (Explained Sum of Squares) and SSR (Residual Sum of Squares) and it is calculated by applying equations such as Formula (3) to Formula (6).

$$R^2 = 1 - \frac{SSR}{SST} \tag{3}$$

$$\mathrm{SST} = \sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2 \tag{4}$$

$$\mathrm{SSE} = \sum_{i=1}^{n} \left(\hat{Y}_i - \overline{Y}\right)^2 \tag{5}$$

$$\mathrm{SSR} = \sum_{i=1}^{n} \hat{u}_i{}^2 \tag{6}$$

Y_i herein refers to the $\mathrm{i_{th}}$ dependent variable and $\overline{Y}$ is the average of Y_i. u_i means the error of regression analysis.

The coefficient of determination (R^2) is a parameter representing the correlation of independent variables with size regarding the total variation of the dependent variable and has the scope of $0 \leq \mathrm{R}^2 \leq 1$. However, a coefficient of determination (R^2) increases as the number of independent variables rise in multiple regression analysis. A revised coefficient of determination of Formula (7) should be applied in the multiple regression analysis in order to improve weak points of this coefficient of determination. In addition, it is necessary to select only the most influential variable among many independent variables and include it in the regression model, or gradually eliminate the least influential variable to dependent variables to simplify the regression formula.

$$R^2_{adj} = 1 - \frac{SSE/(n-k-1)}{SST/(n-1)} \tag{7}$$

n in this formula refers to sample size and k refers to an independent variable.

The Variance Inflation Factor calculates the degree of increasing the divergence of the estimated regression coefficient if an independent variable shows the correlation, as shown in Formula (8). Multicollinearity means that some independent variables of the model are correlated with other independent variables. The bigger multicollinearity means that a single independent variable depends on another independent variable, which violates the assumption of the independent variable. Since it enlarges the divergence of the regression coefficient, destabilizes the model, and makes it unpredictable, it causes a problem. If the divergence expansion coefficient is 1, it means that there is no multicollinearity. If the divergence expansion coefficient is generally over 10, it can be said that there is a problem in collinearity.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{8}$$

R^2 herein refers to a coefficient of determination.

3.2. Correlation Analysis

Correlation analysis is an analysis of measuring the correlation and direction on the linear relationship between two variables in probability theory and statistics. Both variables can show an independent relationship or are correlated. Correlation means the intensity of the relationship between two variables.

Pearson rank-order correlation coefficient, Kendall rank-order correlation coefficient, and Spearman rank-order correlation coefficient analysis methods are typically used in statistics. The correlation coefficient used for identifying the level of correlation does not describe the correlation, but merely shows the relevant degree between two variables. The correlation coefficient is analyzed between −1 and +1. As the correlation coefficient nears ±1, correlation between two variables nears perfect. As it nears 0, there is no correlation between them. The + sign shows a positive correlation and the while-sign shows a negative correlation, according to the direction of correlation.

The pearson linear correlation coefficient is a statistical method measuring the degree of correlation among linearly related variables. It measures how linearity between two variables is high. High linearity with a straight line in the relationship of variables means a high correlation. Formula (9) shows the equation analyzing the Pearson linear correlation coefficient.

$$\mathrm{r} = \frac{\sum_{i=1}^{M}\left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sqrt{\sum_{i=1}^{M}\left(X_i - \overline{x}\right)^2\left(Y_i - \overline{Y}\right)^2}} \tag{9}$$

r = Pearson r correlation coefficient and X_i, Y_i are the $\mathrm{i_{th}}$ sample values of X and Y variables. $\overline{X}$, $\overline{Y}$, and mean values of X and Y variables and M refers to the number of the sample.

The Kendall rank-order correlation coefficient is a statistical method of measuring the non-parametric correlation that measures the dependency between two variables. It calculates the size of the correlation rank-order coefficient between two variables by using data converted with data standards or ranking standards. Formula (10) shows the equation analyzing the Kendall rank-order correlation coefficient.

$$\tau = \frac{N_c - N_d}{\frac{1}{2}N(N-1)} \tag{10}$$

τ in this case, is the Kendall rank-order correlation coefficient. N_c and N_d are the number of concordant pairs and discordant pairs, respectively. N means the size of the variable.

Spearman rank-order correlation coefficient is a statistical method of measuring the non-parametric correlation that measures the dependency between two variables. It does not assume the distribution of data, measures variables with ranking or the size rank-order standard, and calculate the size of rank-order correlation coefficients between two variables. Formula (11) exhibits the equation analyzing the Spearman rank-order correlation coefficient.

$$r_s = 1 - \frac{6\sum d_i^2}{N(N^2-1)} \tag{11}$$

r_s in this formula means Spearman rank-order correlation coefficient and d_i is the difference of $\mathrm{i_{th}}$ values from arranging values of two variables in the order of size. N is the size of the variable.

4. Materials

4.1. Study Area

This study aims to develop a damage prediction formula by using economy indicators by countries, basic indicators, and damage status of natural disasters. Medium variables for developing a damage prediction formula on natural disasters include GDP (Gross Domestic Product), population, areas, and damage status of natural disasters. Medium variables by countries are provided by many different institutions. Analysis can be conducted after investing all documents on medium variables to develop a damage prediction formula.

With regard to medium variables by countries for developing a damage prediction formula of natural disasters, IMF (International Monetary Fund) provides GDP data from 194 countries, UN (United Nations) provides population data from 235 countries, CIA (Central Intelligence Agency) provides area data from 258 countries, and CRED (Center for Research on the Epidemiology of Disasters) damage the status of natural disaster data from 187 countries.

The world is divided into nine continents consisting of more than 230 countries. Countries where natural disasters hit in eight continents except for Antarctica were selected as target regions. Therefore, this study selected 187 countries where all data on medium variables can be applied among target regions for developing a natural damage prediction formula, as shown in Figure 1. Countries selected as target regions are presented in Table A1 (Appendix A).

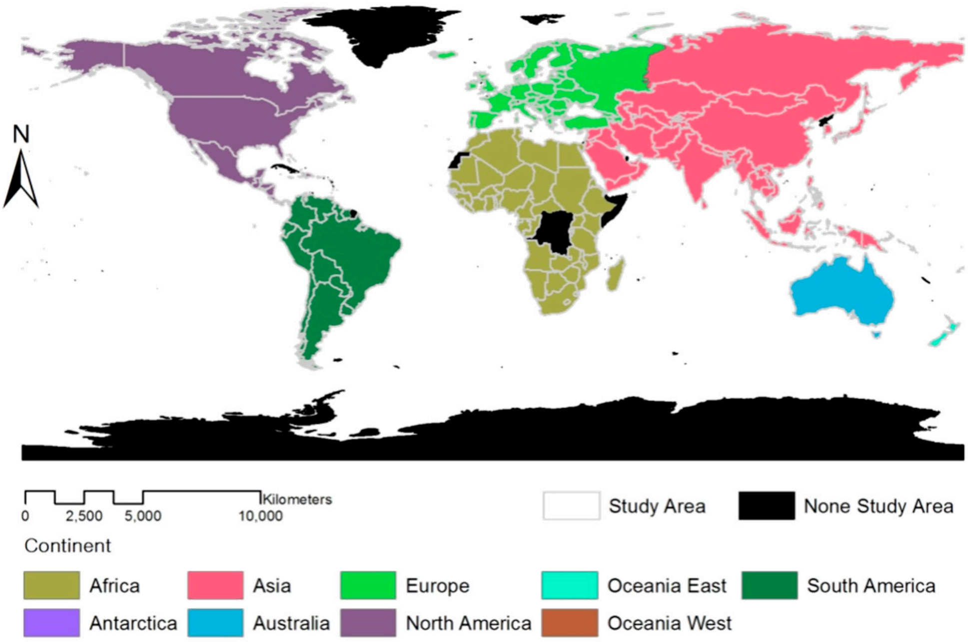


Figure 1. Study area.

4.2. Damage Status of Natural Disasters

CRED resolves health and disputes arisen from disasters, improves preparation and response to disasters, and provides data concerning disaster damage data arisen from national disasters. The CRED collects data associated with disasters through EM-DAT (the Emergency Events Database). As a source of data, data is collected from various institutions such as UN organizations, non-governmental organizations, insurance companies, research institutes, and media outlets. EM-DAT disaster data construction standards include human losses deaths with more than 10 people, human losses affected with more than 100 people, declaring a state of national emergency, and disasters requiring international aids. Human losses affected herein mean the occurrence of disasters, which encompass food, water, shelter, medical assistance, and injured people.

This study aims to analyze damage status by countries from 1900 to 2018 among natural disasters of disaster damage data provided by CRED through EM-DAT. The damage status was investigated by classifying natural disasters into 11 disaster types such as Biological, Climatological, Geophysical, Hydrological, and Meteorological in EM-DAT. The natural disaster damage status was investigated by being classified into human losses from deaths, human losses affected, and damage costs.

The number of natural disasters in the world from 1900 to 2017 was about 13,953. Human losses deaths in the world were about 28,669,875. Human losses affected were 7,845,130,546 and damage costs amount to $3,199,845,668 thousand USD from 1900 to 2017, as shown in Table 1. The damage status of disaster types showed that human losses due to deaths in epidemics, earthquake, and flood account for nearly 85% of entire damages. Human losses affected in drought, flood, and typhoon account for nearly 96% of entire damages. Damage costs in drought, flood, and typhoon account for nearly 90% of entire damages. Tremendous damages were derived from earthquake, flood, and typhoon in the world when natural disasters hit.

Table 1. Damage status of natural disaster types in the world (1900–2017).

Natural Disaster	Year Start	Year Last	Occurrence (count)	Human Losses from Deaths (person)	Human Losses Affected (person)	Damage Costs (thousand U.S. dollars)
Biological	1900	2017	1469	7,092,578	30,600,098	230,132
Epidemic	1900	2017	1385	7,092,578	27,797,898	7
Insect infestation	1913	2010	84		2,802,200	230,125
Climatological	1900	2017	1096	10,495,636	2,641,353,720	244,017,541
Drought	1900	2017	682	10,491,621	2,634,639,788	162,823,266
Wildfire	1911	2017	414	4015	6,713,932	81,194,275
Geophysical	1900	2017	1579	2,490,032	197,244,930	803,217,465
Earthquake	1901	2017	1302	2,419,173	190,655,568	799,086,117
Mass movement	1903	2017	44	4525	19,028	209,000
Volcanic activity	1900	2017	233	66,334	6,570,334	3,922,348
Hydrological	1900	2017	5408	7,023,742	3,768,424,346	760,376,834
Flood	1900	2017	4714	6,970,760	3,754,212,078	751,065,236
Landslide	1909	2017	694	52,982	14,212,268	9,311,598
Meteorological	1900	2017	4401	1,567,887	1,207,507,452	1,392,003,696
Extreme temperature	1936	2017	541	182,776	103,047,180	63,186,343
Storm	1900	2017	3860	1,385,111	1,104,460,272	1,328,817,353
Sum	1900	2017	13,953	28,669,875	7,845,130,546	3,199,845,668

This study aims to analyze the damage status by countries from 1900 to 2017 among natural disasters of disaster damage data provided by CRED through EM-DAT. However, it is difficult to set identical standards on all countries as natural disaster damage data by countries, which vary in disaster occurrence time, disaster size, and data built-up time.

Therefore, this study intends to calculate annual averages on the damage status of natural disaster by countries including human losses due to deaths, human losses affected, and damage costs for developing a natural disaster damage prediction formula. A method of calculating annual averages on damage status of natural disaster by countries is multiplying the total numbers of occurring natural disasters on natural disaster damage with a percentage of observation years, as shown in Formula (12).

$$NDAA_{DCS \cdot HLD \cdot HLA} = \frac{NDD_{DCS \cdot HLD \cdot HLA}}{\sum_{i=year} NDOC_{DCS \cdot HLD \cdot HLA} / DUR(Y_{LO} - Y_{SO} + 1)_{DCS \cdot HLD \cdot HLA}} \tag{12}$$

NDAA herein means Natural Disaster Annual Average. NDD refers to the Natural Disaster Damages, and NDOC refers to the Natural Disaster Occurrence by Country. DUR means Duration. Y_{LO} refers to $Year_{LastestObservations}$ and Y_{so} refers to $Year_{StartObservations}$. DCS means Damage Costs (thousand U.S. dollars) and HLD means Human Losses Deaths (person). HLA is Human Losses Affected (person).

Human losses from deaths, human losses affected, and damage costs were analyzed with regard to the annual average damage of natural disasters by countries. As shown in Figure 2, the scope of damage status was divided into eight segments. The damage status of the annual average damage of natural disasters by countries is shown as follows. (a) The unit of human losses due to deaths is person and 256,805 with the average of 1373 ranging from 0 to 113,787. (b) The unit of human losses affected is person and 77,691,384 with the average of 415,462 ranging from 0 to 29,171,908. (c) The unit of damage costs is thousand U.S. dollars and 32,945,272 with the average of 176,178 ranging from 0 to 8,645,196. Specific annual damage status of natural disasters by countries is shown in Table A2.

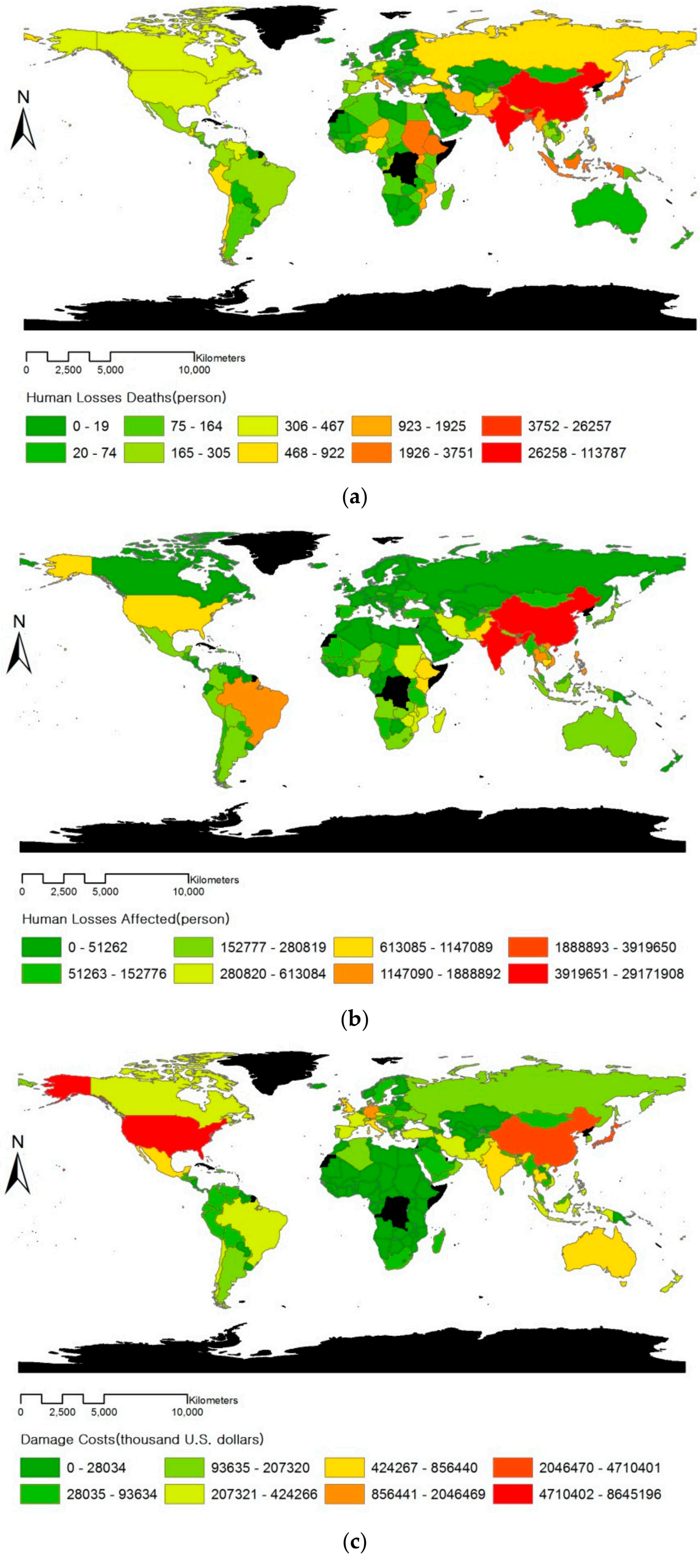


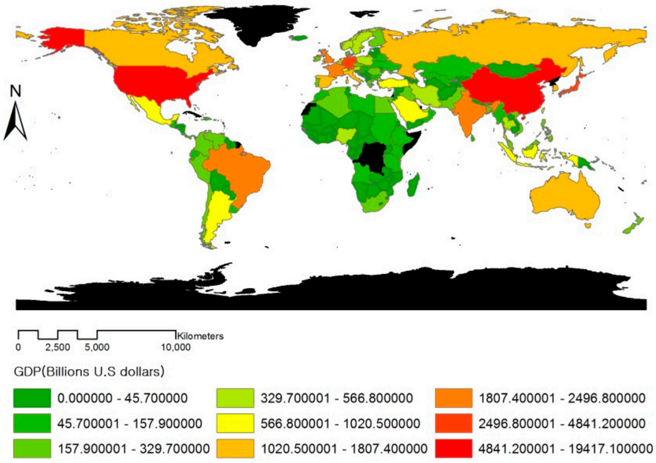
Figure 2. Current state of damage from natural disasters (1900–2017): (**a**) Human losses deaths by countries. (**b**) Human losses affected by countries. (**c**) National disaster damage costs by countries.

4.3. Indicators' Status by Country

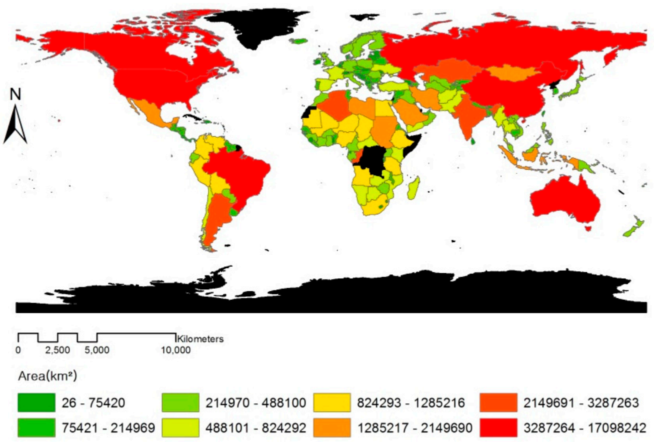
Damages by countries arisen from the occurrence of natural disasters affects damage sizes such as the current status of building urban and social infrastructures, national areas, and population, according to national economic levels. Indicators determining national economic levels include GDP, which is the annual total products by countries, announced by IMF, which is an international organization established for promoting economic development and global trading in 1961. Moreover, The World Factbook by CIA is offered as the area, which is a national basic indicator. Population is provided from World Population Prospects 2017 by UN.

This study analyzed GDP as economic indicators, areas, and population, as basic indicators by setting medium variables by countries for developing a damage prediction formula arisen from occurring natural disasters. Economic indicators and basic indicators by countries are indicators showing the variability of rising or decreasing by years. The present time was applied rather than the past average for developing a damage prediction formula.

Data in 2017 was analyzed regarding GDP, area, and population by countries. The scope by indicators was classified into eight and nine, as shown in Figure 3. The economic indicators and basic indicators status by countries are shown as follows. (a) GDP unit is billions U.S. dollars and 77,815 with the average of 416 ranging from 0.04 to 19,417. (b) Area unit is km^2 and 132,951,506 with the average of 710,971 ranging from 26 to 17,098,242. (c) The population unit is thousands people and 7,567,395 with the average of 40,467 ranging from 11 to 1,415,046. The specific indicator status by countries is presented in Table A2.

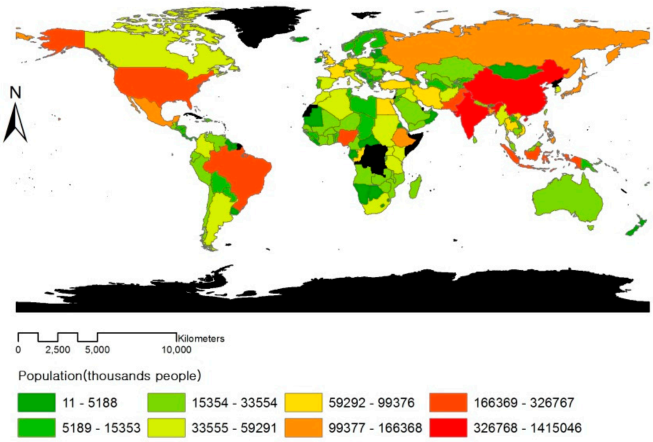


(**a**)



(**b**)

Figure 3. *Cont.*



(**c**)

Figure 3. Current status on economic indicators and basic indicators (2017): (**a**) GDP by countries. (**b**) Areas by countries. (**c**) Population by countries.

5. Results

5.1. Correlation Analysis

For medium variables in order to develop a damage prediction formula of natural disasters, human losses from deaths, human losses affected, and damage costs were selected as a natural disaster damage status. GDP, area, and population were selected as an indicator status by countries. By analyzing the correlation of selected medium variables, it reviewed the appropriateness of developing a damage prediction formula. For a method of correlation analysis, correlation coefficients representing the standard on the distribution, size, and ranking of medium variables on Pearson, Kendall, and Spearman typically used in statistics were selected in this study. Results from analyzing correlation coefficients on the natural disaster damage status and the indicator status by countries are shown in Table 2.

Table 2. Correlation analysis of natural disaster damage status and indicator status by countries.

Parameter	Correlation	GDP	Area	Population	Human Losses Deaths	Human Losses Affected	Damage Costs
GDP	Pearson	1.000	0.552 **	0.554**	0.443 **	0.461 **	0.968 **
	Kendall	1.000	0.390 **	0.551**	0.307 **	0.135 **	0.496 **
	Spearman	1.000	0.547 **	0.736**	0.440 **	0.201 **	0.672 **
	Significant (2-tailed)		0.00	0.00	0.00	0.00	0.00
	N	187	187	187	187	187	187
Area	Pearson	0.552 **	1.000	0.446 **	0.329 **	0.348 **	0.455 **
	Kendall	0.390 **	1.000	0.605 **	0.412 **	0.388 **	0.233 **
	Spearman	0.547 **	1.000	0.790 **	0.578 **	0.553 **	0.339 **
	Significant (2-tailed)	0.00		0.00	0.00	0.00	0.00
	N	187	187	187	187	187	187
Population	Pearson	0.554 **	0.446 **	1.000	0.939 **	0.952 **	0.490 **
	Kendall	0.551 **	0.605 **	1.000	0.567 **	0.457 **	0.362 **
	Spearman	0.736 **	0.790 **	1.000	0.760 **	0.649 **	0.512 **
	Significant (2-tailed)	0.00	0.00		0.00	0.00	0.00
	N	187	187	187	187	187	187
Human Losses Deaths	Pearson	0.443 **	0.329 **	0.939 **	1.000	0.991 **	0.383 **
	Kendall	0.307 **	0.412 **	0.567 **	1.000	0.469 **	0.328 **
	Spearman	0.440 **	0.578 **	0.760 **	1.000	0.653**	0.473 **
	Significant (2-tailed)	0.00	0.00	0.00		0.00	0.00
	N	187	187	187	187	187	187
Human Losses Affected	Pearson	0.461 **	0.348 **	0.952 **	0.991 **	1.000	0.401 **
	Kendall	0.135 **	0.388 **	0.457 **	0.469 **	1.000	0.229 **
	Spearman	0.201 **	0.553 **	0.649 **	0.653 **	1.000	0.332 **
	Significant (2-tailed)	0.00	0.00	0.00	0.00		0.00
	N	187	187	187	187	187	187
Damage Costs	Pearson	0.968 **	0.455 **	0.490 **	0.383 **	0.401 **	1.000 **
	Kendall	0.496 **	0.233 **	0.362 **	0.328 **	0.229 **	1.000 **
	Spearman	0.672 **	0.339 **	0.512 **	0.473 **	0.332 **	1.000 **
	Significant (2-tailed)	0.00	0.00	0.00	0.00	0.00	
	N	187	187	187	187	187	187

** Correlation is significant at the 0.01 level (two-tailed).

The results from analyzing the correlation of medium variables showed a positive correlation in all conditions. Although the number of correlation coefficients by medium variables differs, according to the correlation analysis methods or data characteristics, six medium variables were identified as mutually significant. GDP, damage costs, population, human losses from death, population, and human losses affected showed a higher correlation with over 0.9 in the Pearson correlation regarding correlation coefficients by medium variables. In addition, the area showed a correlation coefficient ranging from 0.3 to 0.8 by medium variables regardless of analytical methods. Thus, the correlation of medium variables selected in this study turned out high. Significant results are considered to be drawn resulting from the interaction of medium variables when the natural disaster damage prediction formula is developed.

5.2. Development of Damage Prediction Equation Considering Human Damage

Multiple regression analysis was performed to develop a damage prediction formula on human losses when natural disasters occur. Human losses arisen from natural disasters are classified into human losses from deaths and human losses affected. By using results from correlation analysis by medium variables, the dependent variables and independent variables were set as shown in Section 4.1.

Multiple regression analysis was conducted by setting dependent variables of a medium variable as human losses from deaths and setting independent variable as GDP, area, and population for developing a damage prediction formula on human losses due to deaths. The results from regression analysis were calculated as shown in Table 3. The adjusted R^2 was 0.893. Three medium variables on human damage losses showed 89.3% higher explanatory powers. Moreover, the significance of using a formula as F = 516.390 of three dependent variables and independent variables, the level of significance as Sig = 0.000 lesser than 0.05 was dramatically higher.

Table 3. Results from multiple regression analysis considering human losses from deaths.

Model Summary					
R	**R Square**		**Adjusted R Square**	**Standard Error of the Estimate**	
0.946[a]	0.894		0.893	3340.632	
ANOVA[b]					
	Sum of Squares	**df**	**Mean Square**	**F**	**Significance**
Regression	17288446415.82	3	5762815471.940	516.390	0.000[a]
Residual	2042246931.16	183	11159819.296		
Total	19330693346.98	186			
Coefficients[b]					
	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Significance**	**VIF**
	B	**Standard Error**	**Beta**			
(Constant)	−975.7353	261.839		−3.726	0.000	
GDP	−0.4389	0.185	−0.075	−2.369	0.019	1.734
Area	0.0004	0.00	−0.084	−2.846	0.005	1.499
Population	0.0702	0.002	1.018	34.518	0.000	1.505

a. Predictors: (Constant), Population, Area, GDP, b. Dependent Variable: Human Losses Deaths.

It analyzed regression coefficients by each variable and multicollinearity indicators on dependent variables of damage prediction formula regarding human losses due to deaths. Regression coefficients by variables on independent variables turned out to be significant as the level of significance through the t-test was less than 1%. However, the level of significance on the regression formula constant numbers was over 20%. If constant numbers are elaborately adjusted, higher R^2 is expected to be calculated. Multicollinearity shows the correlation with independent variables. Since VIF is set to less than 10, the regression coefficient B on independent variables can be trusted. Accordingly, a damage prediction formula on damage costs is shown as Formula (13).

$$\mathrm{HLD} = -975.76353 - 0.4389X_1 + 0.0004X_2 + 0.0702X_3 \tag{13}$$

HLD herein means Human Losses Deaths (person) and X_1 refers to the GDP (billions U.S. dollars). X_2 refers to the Area (km^2) and X_3 means the Population (thousands people).

Dependent variables of medium variables for developing damage prediction formula on damage costs set GDP, area, and population and multiple regression analysis was performed. Results from regression analysis were calculated, as shown in Table 4. The adjusted R^2 on the formula was 0.915. Three medium variables on damage costs had 91.5% higher explanatory powers. Moreover, the significance of using a formula as F = 664.390 of three dependent variables and independent variables, the level of significance as Significance = 0.000 lesser than 0.05 was dramatically higher.

Table 4. Results from multiple regression analysis considering human losses affected.

Model Summary					
R	**R Square**		**Adjusted R Square**		**Standard Error of the Estimate**
0.957a	0.916		0.915		763048.108
ANOVA[b]					
	Sum of Squares	**df**	**Mean Square**	**F**	**Significance**
Regression	1.161×10^{15}	3	3.869×10^{14}	664.504	0.000[a]
Residual	1.066×10^{14}	183	5.822×10^{11}		
Total	1.267×10^{15}	186			
Coefficients[b]					
	Unstandardized Coefficients	**Standardized Coefficients**	**t**	**Significance**	**VIF**
	B / **Standard Error**	**Beta**			
(Constant)	–205644.9682 / 59807.681		–3.438	0.001	(Constant)
GDP	–96.7326 / 42.312	–0.065	–2.286	0.023	GDP
Area	–0.0954 / 0.035	–0.071	–2.721	0.007	Area
Population	18.0191 / 0.465	1.020	38.769	0.000	Population

a. Dependent Variable: Human Losses Affected, b. Dependent Variable: Human Losses Affected.

It analyzed regression coefficients by each variable and multicollinearity indicators on dependent variables of damage prediction formula regarding human losses affected. Regression coefficients by variables on independent variables turned out to be significant as the level of significance through t-test was less than 1%. However, the level of significance on regression formula constant numbers was more than 20%. If constant numbers are elaborately adjusted, higher R^2 is expected to be calculated. Multicollinearity shows the correlation with independent variables. Since VIF is set to less than 10, the regression coefficient B on independent variables can be trusted. Accordingly, a damage prediction formula on damage costs is shown as Formula (14).

$$\mathrm{HLA} = -205644.9682 - 96.7326X_1 - 0.0954X_2 + 18.0191X_3 \tag{14}$$

HLA in this formula means the Human Losses Affected (person) and X_1 refers to GDP (billions U.S. dollars). X_2 means Area (km^2) and X_3 refers to the population (thousands people).

5.3. Development of Damage Prediction Equation Considering Damage Costs

When natural disasters occur, multiple regression analysis was conducted to develop a damage prediction equation considering damage costs. Damage costs from natural disasters set dependent variables and independent variables by using results from correlation analysis by medium variables, as shown in Section 4.1.

Dependent variables of medium variables for developing the damage prediction formula on damage costs set GDP, area, and population. Multiple regression analysis was performed. The results from regression analysis were calculated, as shown in Table 5. The adjusted R^2 on the formula was 0.946. Three medium variables on damage costs had 94.6% higher explanatory powers. Moreover, the significance of using a formula as F = 1088.215 of three dependent variables and independent variables while the level of significance as Significance = 0.000 lesser than 0.05 was dramatically higher.

Table 5. Results from multiple US regression analysis of damage costs.

			Model Summary			
R	**R Square**		**Adjusted R Square**		**Standard Error of the Estimate**	
0.973[a]	0.947		0.946		183379.653	
			ANOVA[b]			
	Sum of Squares		**df**	**Mean Square**	**F**	**Significance**
Regression	1.098×10^{14}		3	3.659×10^{13}	1088.215	0.000[a]
Residual	6.154×10^{12}		183	3.363×10^{10}		
Total	1.159×10^{14}		186			
			Coefficients [b]			
	Unstandardized Coefficients		**Standardized Coefficients**	**t**	**Significance**	**VIF**
	B	**Standard Error**	**Beta**			
(Constant)	17968.0283	14373.290		1.250	0.213	
GDP	476.6021	10.169	1.051	46.869	0.000	1.734
Area	−0.0425	0.008	−0.105	−5.046	0.000	1.499
Population	−0.2442	0.112	−0.046	−2.187	0.030	1.505

a. Predictors: (Constant), Population, Area, GDP, b. Dependent Variable: Damage Costs.

It analyzed regression coefficients by each variable and multicollinearity indicators on dependent variables of the damage prediction formula regarding damage costs. Regression coefficients by variables on independent variables turned out significant since the level of significance through the t-test was less than 1%. However, the level of significance on regression formula constant numbers was more than 20%. If constant numbers are elaborately adjusted, higher R^2 is expected to be calculated. Multicollinearity shows the correlation with independent variables. As VIF is set to less than 10, the regression coefficient B on independent variables can be trusted. Accordingly, a damage prediction formula on damage costs is shown in Formula (15).

$$\mathrm{DCS} = 17968.0283 + 476.6021X_1 - 0.0425X_2 - 0.2442X_3 \tag{15}$$

DCS in this case means Damage Costs (thousand U.S. dollars). X_1, X_2, and X_3 refer to GDP (billions U.S. dollars), Area (km^2), and Population (thousands people), respectively.

6. Discussion

This study developed the damage prediction formula by considering economic indicators among natural disasters. Natural disasters produce the difference of damage sizes, according to the effects of society, economy, and geography even if the same disaster [7,14,23,29]. Earlier studies were mainly conducted to calculate damage costs of each disaster and develop damage prediction functions rather than studying national disaster management [37,38,41]. However, quantitative standards are needed to obtain the size of budgets or relief aids annually planned on comprehensive natural disaster rather than predicting individual disaster damage in terms of disaster management by countries.

This study developed a damage prediction formula on human losses due to deaths, human losses affected, and damage costs of natural disasters and three independent variables of economic indicators by countries such as GDP, population, and area, which were applied in calculating these variables. Adjusted R^2 of the damage prediction formula showed that human losses from deaths mean 0.893, human losses affected mean 0.915, and damage costs mean 0.946 in which higher significance was analyzed. Although previously performed human losses and GDP damage prediction formula were proposed, adjusted R^2 was inefficient ranging from 0.09 to 0.35. Since regression analysis proposed a U-shaped correlation instead of a linear correlation, setting medium variables and methods in this study were appropriate. In addition, there was no significant difference in the correlation of R2 with the calculation formula of various parameters and the formula of GDP. Therefore, it is judged that the application of many parameters does not lead to accurate results [14,15,17]. More data needs to be investigated and built up to be applied in a variety of disasters or countries as single independent variables up to five variables of damage costs and the damage function formula are applied. In addition, only damage costs on the single occurrence by disaster types are calculated, yet quantitative data of budgets and relief aids for disaster management by countries were not analyzed [38–42].

The damage prediction formula in this study is differently applied as units of medium variables, which are human losses and damage costs. The unit of calculation results is person in case of human losses deaths and human losses affected, while thousands of people standard is needed for a national population. Calculating results are thousand U.S. dollars regarding damage costs, while billions U.S. dollars standard is applied in GDP. This mismatch of units by medium variables is assumed to be the limitation of national sizes arisen from data on human losses, damage costs, GDP, population, and area among the world. For further research tasks, it aims to classify grades according to the level of development by countries and developed an estimation formula, according to the annual damage status and the change of economic indicators. If the annual damage status and economic indicators are considered, quantitative indicators for the past, present, and future disaster management, according to the level of national development, are expected to be calculated.

7. Conclusions

This study aimed to consider economic indicators and damage status among natural disasters from 1900 to 2017 in 187 countries, and develop a damage prediction formula of disaster management by countries. For global natural disaster data, this study employed GDP, which is gross domestic product, from EM-DAT operated by CRED from IMF, World Population Prospects 2018 released by the UN, and The World Factbook released from CIA on areas.

Medium variables for developing natural disaster damage prediction formula include human losses from deaths, human losses affected, and damage costs of damage status. Economic indicators by countries and basic indicators include GDP, population, and areas. In total, six medium variables were selected. Damage status of natural disasters considered the number of natural disasters during the period of disaster and calculated average damage costs incurred. Economic indicators and basic indicators were applied based on 2017. Correlation analysis by medium variables was conducted on Pearson, Kendall, and Spearman. Positive correlations were shown in all conditions. Each medium variable and correlation was analyzed to be significant.

A damage prediction formula of natural disaster was analyzed by using multiple regression analysis to calculate annual average damage prediction by applying GDP, population, and areas on human losses from deaths, human losses affected, and damage costs by countries. For a damage prediction formula on human losses due to deaths, the adjusted R^2 turned out 0.893, the level of significance was less than 1%, and VIF was less than 10. Thus, the significance of using the formula was high. A formula on human losses from deaths is summarized as $\mathrm{HLD} = -975.76353 - 0.4389X_1 + 0.0004X_2 + 0.0702X_3$. For a damage prediction formula on the human losses affected, the adjusted R^2 was 0.915, the level of significance was less than 1%, and VIF was less than 10. Thus, the significance of using the formula was high. A formula on human losses affected is summarized as $\mathrm{HLA} = -205644.9682 - 96.7326X_1 - 0.0954X_2 + 18.0191X_3$. For the damage prediction formula on damage costs, the adjusted R^2 turned out to be 0.946 and the level of significance on independent variables was less than 1%. The level of significance on constant numbers is over 20% and VIF was less than 10. Thus, the significance of using the formula was high. A formula on damage costs is $\mathrm{DCS} = 17968.0283 + 476.6021X_1 - 0.0425X_2 - 0.2442X_3$.

The result of this study is considered to be a formula that can be used continuously to predict the damage of natural disaster even in the economic development of the country. The statistical analysis can also predict the damage of natural disasters even in the fluctuation of economy, population, and area by country. There are limitations in applying various parameters such as education, consumption, and facilities except economic indicators by country. However, in the previous studies, various parameters were applied to derive the relationship with natural disasters, but various results were obtained depending on the level of development of the country and the type of disaster. Therefore, the natural disaster damage prediction formula developed in this study is expected to calculate the quantitative damage status of potential natural disasters in accordance with economic indicators by countries, and used as response and preparation data for national disaster management.

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Conflicts of Interest: The authors declare that they have no conflicts of interest in the research.

Appendix A

Table A1. Study area by country.

No	Country	No	Country	No	Country	No	Country	No	Country
1	Afghanistan	39	Cote d'Ivoire	77	Iran	115	Myanmar	153	South Africa
2	Albania	40	Croatia	78	Iraq	116	Namibia	154	South Sudan
3	Algeria	41	Cyprus	79	Ireland	117	Nepal	155	Spain
4	Angola	42	Czech Republic	80	Israel	118	Netherlands	156	Sri Lanka
5	Antigua and Barbuda	43	Democratic Republic of the Congo	81	Italy	119	New Zealand	157	Sudan
6	Argentina	44	Denmark	82	Jamaica	120	Nicaragua	158	Suriname
7	Armenia	45	Djibouti	83	Japan	121	Niger	159	Swaziland
8	Australia	46	Dominica	84	Jordan	122	Nigeria	160	Sweden
9	Austria	47	Dominican Republic	85	Kazakhstan	123	Norway	161	Switzerland
10	Azerbaijan	48	Ecuador	86	Kenya	124	Oman	162	Syria
11	Bahamas	49	Egypt	87	Kiribati	125	Pakistan	163	Taiwan
12	Bahrain	50	El Salvador	88	Korea	126	Palau	164	Tajikistan
13	Bangladesh	51	Equatorial Guinea	89	Kuwait	127	Panama	165	Tanzania
14	Barbados	52	Eritrea	90	Kyrgyzstan	128	Papua New Guinea	166	Thailand
15	Belarus	53	Estonia	91	Lao People's Democratic Republic	129	Paraguay	167	Timor-Leste
16	Belgium	54	Ethiopia	92	Latvia	130	Peru	168	Togo
17	Belize	55	Fiji	93	Lebanon	131	Philippines	169	Tonga
18	Benin	56	Finland	94	Lesotho	132	Poland	170	Trinidad and Tobago
19	Bhutan	57	France	95	Liberia	133	Portugal	171	Tunisia
20	Bolivia	58	FYR Macedonia	96	Libya	134	Puerto Rico	172	Turkey
21	Bosnia and Herzegovina	59	Gabon	97	Lithuania	135	Republic of Congo	173	Turkmenistan
22	Botswana	60	Gambia	98	Luxembourg	136	Romania	174	Tuvalu
23	Brazil	61	Georgia	99	Macao	137	Russian Federation	175	Uganda
24	Brunei Darussalam	62	Germany	100	Madagascar	138	Rwanda	176	Ukraine
25	Bulgaria	63	Ghana	101	Malawi	139	Saint Kitts and Nevis	177	United Arab Emirates
26	Burkina Faso	64	Greece	102	Malaysia	140	Saint Lucia	178	United Kingdom
27	Burundi	65	Grenada	103	Maldives	141	Saint Vincent and the Grenadines	179	United States of America
28	Cabo Verde	66	Guatemala	104	Mali	142	Samoa	180	Uruguay
29	Cambodia	67	Guinea	105	Marshall Islands	143	Sao Tome and Principe	181	Uzbekistan
30	Cameroon	68	Guinea-Bissau	106	Mauritania	144	Saudi Arabia	182	Vanuatu
31	Canada	69	Guyana	107	Mauritius	145	Senegal	183	Venezuela
32	Central African Republic	70	Haiti	108	Mexico	146	Serbia	184	Vietnam
33	Chad	71	Honduras	109	Micronesia	147	Seychelles	185	Yemen
34	Chile	72	Hong Kong SAR	110	Moldova	148	Sierra Leone	186	Zambia
35	China	73	Hungary	111	Mongolia	149	Singapore	187	Zimbabwe
36	Colombia	74	Iceland	112	Montenegro	150	Slovakia		
37	Comoros	75	India	113	Morocco	151	Slovenia		
38	Costa Rica	76	Indonesia	114	Mozambique	152	Solomon Islands		

Table A2. Annual current state of damage from natural disasters and economic indicators and basic indicators by country.

Country Name	GDP (Billions)	Area (km^2)	Population (thousands people)	Human Losses Deaths (person)	Human Losses Affected (person)	Damage Costs (thousand U.S. dollars)
Afghanistan	20.6	652,230	36,373	380	151,400	9,426.9
Albania	12.3	28,748	2,934	4	81,879	658.3
Algeria	173.9	2,381,741	42,008	109	21,389	109,396.7
Angola	122.4	1,246,700	30,774	164	195,955	324.3
Antigua and Barbuda	1.5	443	103	0	1866	11,670.6
Argentina	628.9	2,780,400	44,689	157	203,752	156,586.6
Armenia	10.7	29,743	2934	0	19,795	10,072.7
Australia	1,359.7	7,741,220	24,772	28	205,784	667,795.9
Austria	383.5	83,871	8752	12	1100	100,348.0
Azerbaijan	38.6	86,600	9924	4	143,071	11,733.3
Bahamas	9.2	13,880	399	1	447	36,359.8
Bahrain	34.3	760	1,567	111	0	0.0
Bangladesh	248.9	148,460	166,368	26,257	3,919,650	173,796.3
Barbados	4.8	430	286	1	173	1701.6
Belarus	54.7	207,600	9452	3	6384	7107.2
Belgium	462.7	30,528	11,499	24	127	20,361.5
Belize	1.8	22,966	382	22	3,913	7,436.1
Benin	8.8	112,622	11,486	33	115,689	190.8
Bhutan	2.3	38,394	817	11	3236	129.6
Bolivia	39.3	1,098,581	11,216	42	164,184	72,648.4
Bosnia and Herzegovina	16.8	51,197	3504	3	83,186	48,328.2
Botswana	15.6	581,730	2333	13	29,369	982.1
Brazil	2,140.9	8,515,770	210,868	184	1,507,355	321,219.7
Brunei Darussalam	12.3	5765	434	0	0	2,000.0
Bulgaria	52.3	110,879	7037	4	800	16,139.8
Burkina Faso	12.3	274,200	19,752	160	122,876	1677.6
Burundi	3.4	27,830	11,216	29	114,809	375.0
Cabo Verde	1.6	4033	553	735	769	35.3
Cambodia	21.0	181,035	16,246	82	764,997	51970.3
Cameroon	29.5	475,440	24,678	128	22,436	110.6
Canada	1,600.3	9,984,670	36,954	451	22,675	280,353.0
Central African Republic	2.0	622,984	4737	21	5133	2.8
Chad	9.6	1,284,000	15,353	96	104,295	871.8
Chile	251.2	756,102	18,197	549	111,438	367,669.4
China	11,795.3	9,596,960	1,415,046	113,787	29,171,908	4,710,401.3
Colombia	306.4	1,138,910	49,465	305	161,920	63,968.5
Comoros	0.7	2235	832	6	4,636	426.8
Costa Rica	59.8	51,100	4953	21	17,787	12,593.4
Cote d'Ivoire	36.9	322,463	24,906	19	732	0.0
Croatia	50.1	56,594	4165	39	945	38,579.5
Cyprus	19.6	9251	1189	2	107	262.5
Czech Republic	196.1	78,867	10,625	27	73,743	271,227.8
Democratic Republic of the Congo	41.1	2,344,858	84,005	213	45,146	600.0
Denmark	304.2	43,094	5754	1	0	136,753.7
Djibouti	2.1	23,200	971	10	55,357	168.2
Dominica	0.5	751	74	24	2232	25,262.0

Table A2. *Cont.*

Country Name	GDP (Billions)	Area (km^2)	Population (thousands people)	Human Losses Deaths (person)	Human Losses Affected (person)	Damage Costs (thousand U.S. dollars)
Dominican Republic	76.9	48,670	10,883	66	85,847	34,029.9
Ecuador	97.4	283,561	16,863	134	46,799	51,055.3
Egypt	236.5	1,001,450	99,376	133	4139	16,274.7
El Salvador	27.5	21,041	6,412	66	38,967	57,869.1
Equatorial Guinea	11.7	28,051	1314	15	946	0.0
Eritrea	6.1	117,600	5188	0	351,418	322.8
Estonia	23.4	45,228	1307	1	13	16,250.0
Ethiopia	78.4	1,104,300	107,535	3,751	725,147	13,683.7
Fiji	4.9	18,274	912	7	23,337	14,927.1
Finland	234.5	338,145	5543	0	25	625.0
France	2420.4	643,801	65,233	233	38,007	399,501.8
FYR Macedonia	11.0	25,713	2085	3	51,262	16,366.5
Gabon	14.2	267,667	2068	5	4435	0.0
Gambia	1.0	11,300	2164	4	13,559	6.6
Georgia	13.7	69,700	3907	3	35,518	28,034.2
Germany	3,423.3	357,022	82,293	347	20,595	2,046,468.9
Ghana	42.8	238,533	29,464	22	221,455	1,522.8
Greece	193.1	131,957	11,142	28	11,900	145,918.4
Grenada	1.1	344	108	1	1275	18,843.8
Guatemala	70.9	108,889	17,245	728	111,744	38,176.4
Guinea	6.9	245,857	13,053	107	12,760	0.0
Guinea-Bissau	1.2	36,125	1907	30	2,998	0.0
Guyana	3.6	214,969	782	1	27,197	14,425.5
Haiti	7.9	27,750	11,113	2293	177,206	104,567.6
Honduras	21.8	112,090	9417	277	62,888	50,328.9
Hong Kong SAR	332.3	1,108	7429	219	1310	11,928.1
Hungary	125.3	93,028	9689	22	5349	40,841.7
Iceland	23.0	103,000	338	1	152	1,868.1
India	2,454.5	3,287,263	1,354,052	77,390	20,345,983	789,199.2
Indonesia	1,020.5	1,904,569	266,795	2,179	276,959	268,204.8
Iran	368.5	1,648,195	82,012	1,439	411,553	225,914.6
Iraq	189.4	438,317	39,340	3	16,610	957.8
Ireland	294.2	70,273	4,804	1	179	19,372.9
Israel	340.0	20,770	8453	2	44,365	31,973.4
Italy	1,807.4	301,340	59,291	1,247	35,632	856,440.4
Jamaica	14.3	10,991	2899	23	24,538	24,306.1
Japan	4,841.2	377,915	127,185	2,075	167,674	3,902,597.5
Jordan	40.5	89,342	9904	8	4675	5,307.9
Kazakhstan	157.9	2,724,900	18,404	9	32,066	11,422.8
Kenya	75.1	580,367	50,951	125	1,147,089	4812.7
Kiribati	0.2	811	118	0	1,974	0.0
Korea	1498.1	99,720	51,164	110	83,383	199,308.0
Kuwait	127.0	17,818	4197	0	29	0.0
Kyrgyzstan	6.9	199,951	6133	18	87,537	8375.4
Lao People's Democratic Republic	15.0	236,800	6961	28	198,207	11,107.9
Latvia	27.8	64,589	1930	7	7	23,250.0

Table A2. *Cont.*

Country Name	GDP (Billions)	Area (km^2)	Population (thousands people)	Human Losses Deaths (person)	Human Losses Affected (person)	Damage Costs (thousand U.S. dollars)
Lebanon	53.9	10,400	6094	10	18,442	2,704.9
Lesotho	2.4	30,355	2263	3	79,869	20.4
Liberia	2.2	111,369	4854	148	43,078	1,270.3
Libya	54.4	1,759,540	6471	5	29	674.3
Lithuania	42.8	65,300	2876	5	37,143	14,932.0
Luxembourg	60.0	2,586	590	6	0	15,035.7
Macao	45.7	28	632	0	167	56,800.0
Madagascar	10.4	587,041	26,263	100	347,624	4,6436.0
Malawi	6.2	118,484	19,165	61	613,084	8833.1
Malaysia	309.9	329,847	32,042	27	73,918	44,322.7
Maldives	3.6	298	444	10	1,928	14,885.3
Mali	14.3	1,240,192	19,108	38	67,701	0.0
Marshall Islands	0.2	181	53	0	1382	196.0
Mauritania	5.1	1,030,700	4540	2	106,530	569.4
Mauritius	12.2	2040	1268	2	19,111	14,877.3
Mexico	987.3	1,964,375	130,759	267	230,682	593,654.0
Micronesia	0.3	702	106	3	5,869	583.3
Moldova	7.4	33,851	4041	5	152,776	42,114.9
Mongolia	10.3	1,564,116	3122	25	76,182	32,789.6
Montenegro	4.2	13,812	629	0	1144	0.0
Morocco	105.6	446,550	36,192	135	33,290	18,818.0
Mozambique	11.2	799,380	30,529	1714	557,839	18,542.7
Myanmar	72.4	676,578	53,856	1263	83,202	41,960.5
Namibia	11.8	824,292	2,588	15	90,509	5,430.3
Nepal	23.3	147,181	29,624	394	208,241	77,751.8
Netherlands	762.7	41,543	17,084	63	8833	88,667.2
New Zealand	198.0	268,838	4750	74	6704	307,300.4
Nicaragua	13.7	130,370	6285	154	40,911	24,553.2
Niger	7.7	1,267,000	22,311	1700	258,194	2365.6
Nigeria	400.6	923,768	195,875	573	280,819	14,663.8
Norway	392.0	323,802	5353	1	88	7407.9
Oman	71.3	309,500	4830	7	807	126,146.3
Pakistan	305.0	796,095	200,814	1925	995,626	308,793.1
Palau	0.3	459	22	0	625	0.0
Panama	59.5	75,420	4163	7	6957	5825.0
Papua New Guinea	21.2	462,840	8418	84	48,654	3104.7
Paraguay	28.7	406,752	6897	6	67,429	2843.6
Peru	207.1	1,285,216	32,552	922	221,854	60,997.6
Philippines	329.7	300,000	106,512	619	1,888,892	233,112.3
Poland	482.9	312,685	38,105	26	4212	93,633.9
Portugal	202.8	92,090	10,291	78	4089	146,062.2
Puerto Rico	99.7	9104	3659	15	9302	717,280.0
Republic of Congo	8.3	342,000	5400	19	4054	1.3
Romania	189.8	238,391	19,581	45	18,668	55,590.2
Russian Federation	1560.7	17,098,242	143,965	616	44,289	112,730.0
Rwanda	8.9	26,338	12,501	22	140,238	0.2
Saint Kitts and Nevis	1.0	261	56	0	159	7832.2

Table A2. *Cont.*

Country Name	GDP (Billions)	Area (km^2)	Population (thousands people)	Human Losses Deaths (person)	Human Losses Affected (person)	Damage Costs (thousand U.S. dollars)
Saint Lucia	1.4	616	180	1	5476	2442.9
Saint Vincent and the Grenadines	0.8	389	110	15	822	1622.6
Samoa	0.8	2,831	198	9	7659	15,694.8
Sao Tome and Principe	0.4	964	209	9	4148	0.0
Saudi Arabia	707.4	2,149,690	33,554	12	606	31,518.5
Senegal	15.4	196,722	16,294	14	97,034	4,011.5
Serbia	37.7	77,474	8762	9	19,136	207,320.2
Seychelles	1.5	455	95	0	1301	2050.0
Sierra Leone	4.1	71,740	7720	156	7448	781.4
Singapore	291.9	697	5792	2	849	0.0
Slovakia	89.1	49,035	5450	10	2829	37,409.5
Slovenia	43.5	20,273	2081	18	3936	44,235.3
Solomon Islands	1.2	28,896	623	9	5180	581.4
South Africa	317.6	1,219,090	57,398	23	219,750	55,949.7
South Sudan	4.8	644,329	12,919	49	1,006,103	0.0
Spain	1232.4	505,370	46,397	266	105,370	424,266.1
Sri Lanka	84.0	65,610	20,950	655	502,821	73,366.6
Sudan	115.9	1,861,484	41,512	2096	443,066	7156.4
Suriname	3.6	163,820	568	0	904	1.3
Swaziland	3.9	17,364	1391	21	89,478	1645.3
Sweden	507.0	450,295	9983	1	11	83,073.7
Switzerland	659.4	41,277	8544	21	148	122,384.5
Syria	24.6	185,180	18,284	4	38,409	898.0
Taiwan	566.8	35,980	23,694	197	35,277	198,705.5
Tajikistan	7.2	144,100	9107	79	241,980	64,478.0
Tanzania	51.2	947,300	59,091	89	121,856	3998.2
Thailand	432.9	513,120	69,183	239	1,707,325	83,4014.4
Timor-Leste	2.7	14,874	1324	2	8486	250.0
Togo	4.6	56,785	7991	23	22,258	13.5
Tonga	0.4	747	109	0	2880	1731.0
Trinidad and Tobago	21.7	5128	1373	1	682	822.1
Tunisia	40.3	163,610	11,659	16	9650	7226.2
Turkey	793.7	783,562	81,917	801	77,849	239,218.3
Turkmenistan	42.4	488,100	5851	1	53	12,483.8
Tuvalu	0.0	26	11	0	140	0.0
Uganda	27.2	241,038	44,271	1750	55,397	685.2
Ukraine	95.9	603,550	44,009	57	109,685	128,831.3
United Arab Emirates	407.2	83,600	9542	0	188	0.0
United Kingdom	2496.8	243,610	66,574	26	11,629	566,472.4
United States of America	19,417.1	9,833,517	326,767	373	964,231	8,645,195.8
Uruguay	58.1	176,215	3470	1	5134	7196.1
Uzbekistan	68.3	447,400	32,365	4	32,602	2500.0
Vanuatu	0.8	12,189	282	5	6929	418.6
Venezuela	251.6	912,050	32,381	467	16,517	54,319.8
Vietnam	215.8	331,210	96,491	411	1,450,242	332,328.8
Yemen	27.2	527,968	28,915	43	22,152	67,092.6
Zambia	23.1	752,618	17,609	35	235,579	522.5
Zimbabwe	15.3	390,757	16,913	161	469,882	24,132.6

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