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# A Strategic Framework for Natural Disaster-Induced Cost Risk Analysis and Mitigation: A Two-Stage Approach Using Deep Learning and Cost-Benefit Analysis

Ji-Myong Kim[1], Sang-Guk Yum[2], Hyunsoung Park[3], and Junseo Bae[4]

[1]Department of Architectural Engineering, Mokpo National University, Mokpo 58554, South Korea; jimy6180@gmail.com
[2]Department of Civil Engineering, Gangneung-Wonju National University, Gangneung 25457, South Korea; skyeom0401@gwnu.ac.kr
[3]Department of Mechanical and Civil Engineering, University of Evansville, Evansville, Indiana 47722, United States; hp93@evansville.edu
[4]School of Computing, Engineering and Physical Sciences, University of the West of Scotland, Paisley PA1 2BE, United Kingdom; junseo.bae@uws.ac.uk

*Correspondence to*: Junseo Bae (junseo.bae@uws.ac.uk)

**Abstract.** Due to gradual increases in the frequency and severity of natural disasters, risks to human life and property from natural disasters are exploding. To reduce these risks, various risk mitigation activities have been widely conducted. Risk mitigation activities are becoming more and more important for economic analysis of risk mitigation effects due to limited public budget and the need for economic development. To respond to this urgent need, this study aims to develop a strategic evaluation framework for natural disaster risk mitigation strategies. The proposed framework predicts natural disaster losses using a deep learning algorithm (stage I) and introduces a new methodology that quantifies the effect of natural disaster reduction projects adopting cost-benefit analysis (stage II). To achieve the main objectives of this study, data of insured loss amounts due to natural disasters associated with the identified risk indicators were collected and trained to develop the deep learning model. The robustness of the developed model was then scientifically validated. To demonstrate the proposed quantification methodology, reservoir maintenance projects affected by floods in South Korea were adopted. The results and main findings of this study can be used as valuable guidelines to establish natural disaster mitigation strategies. This study will help practitioners quantify the loss from natural disasters and thus evaluate the effectiveness of risk reduction projects. This study will also assist decision-makers to improve the effectiveness of risk mitigation activities.

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# 1 Introduction

## 1.1 Natural disaster and risk

The frequency and intensity of extreme weather events due to climate change are rapidly increasing, causing various damages. These damages are expected to affect extreme weather events in the short term, with various long-term effects such as sea level rise and disease spread. Examples of extreme weather events include flooding, drought, heavy rain, tropical cyclone, heat waves, and cold waves. These extreme weather events are rapidly increasing losses associated with their increases in frequency and intensity. Increases of these losses are causing many economic losses worldwide. For example, Western European countries such as France, Germany, and Switzerland were hit by three consecutive tropical cyclones (e.g., Anatol, Lothar, and Martin) in 1999, resulting in a loss of 13 billion euros (Ulbrich et al., 1999). Typhoon Haiyan, which hit the Philippines and China of South Asia in 2013, was one of Category 5 Super Typhoons, was the most extreme tropical cyclone recorded on land. The typhoon's life-threatening wind and rain were enough to smash properties. South Asian countries adjacent to the typhoon track inflicted about $300 billion in damage (Kim et al., 2019). Hurricane Katrina, which hit the southeastern United States in 2005, caused the most damage in American history. Hurricane Katrina was a Category 5 tropical cyclone that had caused the US Gulf Coast city to have $180 billion in direct and indirect damage due to substantial rain and robust winds (Blake et al., 2007). In the United States in 2017, three powerful hurricanes (Harvey, Maria, and Irma) caused a total damage of about $293 billion, with Harvey causing $125 billion in damage, Maria causing $90 billion, and Irma $77.6 billion (USNHC, 2018).

Moreover, over the past century, the severity and frequency of natural disasters worldwide have increased. Climate anomalies have also increased. The Intergovernmental Panel on Climate Change (The Fifth Assessment Report, 2014) has already warned of an increase in global average temperature, average sea level escalation, heating, and acidification. In many countries, severe weather events such as typhoons and heavy rains and changing patterns of meteorological disasters have already increased the loss of many lives and property. These damages are expected to accelerate in the future (Kim et al., 2020).

Therefore, lives and property worldwide are threatened by natural disasters. Such threats will increase. To reduce these threats, numerous non-governmental organizations and countries are investing a lot of time, budget, and manpower to mitigate risks from natural disasters. Mitigation of risks can reduce the loss by decreasing vulnerability or by decreasing the frequency and severity of causal factors (Rose et al., 2007). For risk mitigation, the execution of financial resources should be carried out quickly and extensively. In practice, the efficiency and amounts of financial resources should be considered due to limited resources. Hence, it is important to grasp the amount of risk and the effect of risk reduction at the same time to achieve the ultimate reduction and mitigation of risk through an efficient use of limited resources. In other words, it is essential for risk mitigation against potential risks by predicting the exact amount of risk, which aims to make an active investment to reduce the predicted risk, and to find out the economic effect of the risk reduction. Consequently, as part of a case study on risk mitigation costs, this study developed a strategic framework by developing a natural disaster damage prediction model using

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deep learning algorithms and proposing a methodology to quantify the effect of natural disaster reduction through cost-benefit analysis.

**1.2 Natural disaster loss quantification**

Given the frequency and severity of natural disasters, the demand for sophisticated natural disaster loss forecasting also increases. In response to such demand, various companies and national organizations have developed models to predict natural disaster losses. The New Multi-Hazards and Multi-Risk Assessment Method for Europe (MATRIX) in Europe, the HAZUS-Multi Hazard (HAZUS-MH) by the Federal Emergency Management Agency (FEMA) in the United States, the RiskScape in New Zealand, and the Probabilistic Risk Assessment initiative in Central America are representative models (Kim et al., 2017). Florida, USA, has developed a Florida Public Hurricane Loss Model (FPHLM) to predict losses due to hurricanes as it is located on the main north-facing road of hurricanes (Kim et al., 2020). These models are being used in different regions to assess the loss of life and potential economic losses for buildings and infrastructure owing to natural disasters. Nevertheless, since these models were developed based on the vulnerability of natural disasters and the severity and frequency of natural disasters in specific areas, they could not be applied to other areas.

Companies specializing in natural disaster risk modeling have also developed different models, including EQECAT, Applied Insurance Research (AIR), and RMS (Risk Management Solution) (Kunreuther et al., 2004; Sanders, 2002). These models are widely used by insurers and reinsurers around the world to assess the risk of economic loss from natural disasters (e.g., windstorms, earthquakes, floods, earthquakes, winter storms, and tornadoes). Nonetheless, these models have annual fees that are expensive to small and medium-sized users. In addition, these models are available only for the limited number of major countries (Europe, USA, Japan, China, etc.). In addition, it is difficult to optimize them for users since they have difficulties to reflect a user's portfolio, capital, business preference, and so on (Kim et al., 2019).

To reflect characteristics and vulnerabilities of each country associated with various situations of users, it is crucial to evaluate the loss through its own model. In order to develop a loss evaluation model, the development of an in-house model using a deep learning algorithm can be a solution. Recently, the 4th revolution technology (e.g., unmanned transportation, big data, artificial intelligence, IoT, robots, etc.) has been applied to various fields and its effectiveness has been recognized (Gledson and Greenwood, 2017; IPA, 2017). To effectively and efficiently analyze the complexity of various sensors-driven big data, the demand for deep learning applications has been increased dramatically. In this sense, this study proposed a framework for developing a natural disaster risk quantification model based on deep learning technology to predict losses due to natural disasters.

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### 1.3 Cost-benefit analysis of natural disaster risk mitigation

Mitigating the risk with efficient investment and operation of resources is a challenging task because resources are finite while risk reduction should be done quickly and extensively. To address these issues, cost-benefit analysis has been widely adopted (FEMA, 2005; Rose et al., 2007). For instance, efficient use of public resources is indicated when total estimated profits of a risk mitigation activity surpass the entire cost or are parallel to earnings on investment of both private and public.

Disaster risk mitigation represents mitigating social, environmental, and economic damage caused by natural disasters. Since economic losses due to natural disasters are hard to minimize or avoid separately, there is an increasing public demand for risk reduction investments to reduce these economic losses (Bouwer et al., 2007; Shreve and Kelman, 2014). Since resources for risk mitigation investment are restricted, it is critical to estimate economic costs and benefits in order to determine the effectiveness and appropriateness of the investment. For instance, the Federal Emergency Management Agency of the United States has reported that the average benefit cost ratio is 4 for risk mitigation investment (e.g., structural defense measures against floods and typhoons, building renovations in preparation for earthquakes, etc.) after reviewing 4,000 natural disaster risk reduction programs in the United States ( Kunreuther et al., 2012; Rose et al., 2007). In addition, studies in developing countries have shown a high benefit cost ratio in a study of 21 investment activities such as re-establishment of schools and forestry in preparation for tsunami (Bouwer et al., 2014).

Despite these high potential benefits, investment in risk reduction for residents living in areas at risk of natural disasters is restricted (Bouwer et al., 2014). According to Hochrainer-Stigler et al. (2010), since natural disaster risk reduction measures are focused on short-term outcomes, only about 10% of residents in areas vulnerable to natural disasters receive natural disaster risk reduction measures in the United States. In the case of a natural disaster risk reduction project, a large initial investment is required, which reduces the expected profit if performance indicators need to be met in a short period of time. As a result, policy makers and politicians are reluctant to make bold investments in natural disaster risk reduction. They prefer to provide economic support after disasters (Cavallo et al., 2013). This phenomenon is also reflected in the budget distribution of disaster management funds of donations and development agencies. Most (98%) of the budget is allocated to reconstruction or relief. Only the remaining budget (2%) is allocated to risk reduction (Mechler, 2005). As such, while the need for pre-disaster risk reduction through proactive disaster investment is widely recognized, the economic impact of natural disaster risk reduction is often not fully considered in decision-making. Moreover, although cost-benefit analysis (CBA) is the main decision-making tool commonly used in public sector investment and financial evaluation, natural disaster risk is not sufficiently applied in CBA (Hochrainer-Stigler et al., 2010). Natural disasters in public sector investment projects are often overlooked or not evaluated in CBA assessments (Kreimer et al., 2003). Hence, in this study, the effectiveness of a natural disaster reduction project was determined through a case study of cost-benefit analysis conducted by the Korean government is considered and a methodology for calculating dismissal was presented.

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## 2 Research objectives and methods

To reduce economic losses caused by natural disasters, it is necessary to quantify losses caused by natural disasters and make active investments to reduce risks. Therefore, for economic analysis of losses from natural disasters, this study attempted to examine the investment effects, predict losses caused by natural disasters. The main objectives of this study are to develop a strategic framework that predicts natural disaster losses using a deep learning algorithm and introduces a methodology to quantify the effect of natural disaster reduction projects using cost-benefit analysis. To achieve the main objective of this study, a two-stage approach was adopted.

In Stage I, this study collected reliable storm and flood damage insurance data and natural disaster risk indicators, created a predictive model based on a deep learning algorithm, and verified. This study proposed a deep learning modeling framework that could accurately learn and predict multiple natural disaster indicators known to affect losses caused by natural disasters. The first research objective was achieved through the following steps:

1) To collect data on loss caused by natural disasters, this study collected data on claim payout for storm and flood damage insurance from the Korea Insurance Development Institute (KIDI) over the past11 years between 2009 and 2019.
2) This study obtained natural disaster risk indicators based on the collected data.
3) A model of deep learning algorithm was developed using Python 3.7, Keras, and Scikit-Learn libraries. The model was trained, tested, and validated using the collected data.
4) A multiple regression model was independently developed using IBM Statistical Package for the Social Sciences (SPSS) version 23 for model validation.
5) The root mean squared error and mean absolute error values of the deep learning algorithm model and the multiple regression analysis model were estimated and paralleled, respectively.

In Stage II, data on natural disaster risk reduction projects conducted by national institutions were collected and cost-benefit analysis was performed for cost of natural disaster risk reduction. This study intended to propose a framework for quantifying the economic cost of natural disaster risk reduction. To realize the goal of this study, the following steps were used. In addition, this study intended to propose a framework for quantifying the economic cost of natural disaster risk reduction. The second objective of this study was achieved through the following steps:

1) Among natural disaster risk reduction projects carried out by the South Korean government, information on disaster risk reservoir maintenance projects completed in 2009-2019 was collected.
2) The loss rate of storm and flood insurance in the region where the flood damage occurred after the completion of the maintenance project was investigated through the Korea Insurance Development Institute (KIDI).
3) The amount of precipitation before and after the disaster risk reservoir maintenance project was investigated.
4) Cost-benefit analysis was conducted to determine the economic feasibility of the maintenance project.

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## 3 Stage I: Development of a natural disaster loss prediction model

### 3.1 Data collection

This section develops and validates a deep learning algorithm model that can efficiently and accurately predict losses due to natural disasters based on data about the loss amount of flood insurance with high reliability. To collect such data, this study used KIDI's storm and flood damage insurance claims for 11 years from 2009 to 2019. KIDI was established in 1983. It is an insurance professional service organization that develops insurance products, calculates insurance rates, and protects the rights of policyholders. It also collects and manages various statistical data such as insurance information and losses of each insurance company (Choi and Han, 2015). Storm and flood damage insurance, which reflects the loss amount, is an insurance that compensates for property damage caused by natural disasters (e.g., typhoons, floods, heavy rains, tsunamis, strong winds, storms, heavy snow, earthquakes, and so on). It has been implemented since 2006 under the initiative of state and local governments (Kwon and Oh, 2018). The insurance payout amount is determined by objective analysis of certified loss assessment service according to standardized procedures for each insurance company. Its reliability is high (Kim et al., 2020). The prediction model was trained, tested, and validated using losses and natural disaster risk indicators.

The cost of loss due to natural disasters was divided by the total net premiums to calculate the ratio and then log-transformed. In addition, natural disaster risk indicators affecting insurance loss due to natural disasters were collected. For natural disaster risk indicators, building type, wind speed, total rainfall, and peak ground acceleration were selected as variables through past literature studies (Kim et al., 2017, 2019; Kim et al., 2020; Kim et al., 2021). A description of variables is presented in Table 1. Building types were set as dummy variables that consist of residential buildings and greenhouses. Wind speed and the maximum value of rainfalls were collected from the Korea Meteorological Administration (KMA). Peak ground accelerations were collected from the National Oceanic and Atmospheric Administration (NOAA). Descriptive statistics of variables are displayed in Table 2.

Table 1. Description of variables

| Variable | Explanation |
|---|---|
| Loss ratio | Total loss divided by the total net premium (KRW, log-transformed) |
| Building type | Buildings covered by storm and flood insurance<br>(Categorical variable - Residential building: 1; Greenhouse: 2) |
| Wind speed | 10-minute average maximum wind speed (m/s) |
| Rainfall | Maximum precipitation per day (mm/day) |
| Peak Ground Acceleration | Value of Peak Ground Acceleration (PGA) (g) |

Table 2. Descriptive statistics of variables

| Variable (unit) | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Loss ratio (log-transformed KRW) | 458 | -5.12 | 3.17 | -0.66 | 1.01 |
| Building type (1: residential; 2: greenhouse) | 458 | - | - | - | - |
| Wind speed (m/s) | 458 | 20.80 | 39.20 | 29.21 | 3.17 |
| Rainfall (mm/day) | 458 | 172.00 | 801.20 | 319.02 | 68.57 |
| Peak ground acceleration (g) | 458 | 0.10 | 1.60 | 1.10 | 0.25 |

### 3.2 Modelling deep neural networks

A deep learning algorithm is a neural network with many layers and various structures in general. Its use in research and industry for prediction and recognition has spread rapidly, proving its effectiveness (Kim et al., 2021). Deep learning algorithms are also widely used for regression analysis and type classification as a machine learning technique (Ajayi et al., 2019). Deep learning models have the same training framework as other types of neural networks. However, they can train large data sets more effectively with multiple hidden layers (Bae et al., 2021). Deep learning algorithms can be divided into deep neural network (DNN), generative adversarial network (GAN), recurrent neural network (RNN), convolutional neural network (CNN), and auto encoder (AE) according to their structure and processing method (Kim et al., 2021). Especially, DNN is used for cataloguing and prediction in various engineering and academic fields (Krizhevsky et al., 2012; Toya and Skidmore, 2007). Moreover, DNNs can be applied to train and model complex nonlinear relationships due to their multi-layered structures. Thus, in this study, a DNN model was accepted considering nonlinearity of collected loss data.

The learning performance of the model was appraised by measuring the values of root mean squared error (RMSE) and mean absolute error (MAE). RMSE and MAE are representative indicators of the size of the error by comparing the predicted result of an artificial neural network with the actual value (Daniell et al., 2011). RMSE is a value that measures the average error magnitude. MAE is a value obtained by converting the difference between the actual value and the predicted value into an absolute value and averaging it. Both indicators can be used to indicate that the prediction error decreases as the error value gets smaller (e.g., closer to zero).

The collected loss data were pre-processed using a z-score normalization method to adjust the unit and quantity of the data. The pre-processed completed input data were divided into a training set, a verification set, and a test set of data. The training set of data were used for learning of the DNN algorithm. The verification set of data were used to judge whether training was optimal and the test set of data were used to verify whether the developed model was finally trained for the purpose. In this study, considering the amount of data, 70% of the total data were set as training set of data and 30% of them were used as test set of data. Then 30% of training data were utilized as verification data.

The DNN model selected the optimal combination through a trial-and-error method since the DNN model could update the weights of neural network nodes with a backpropagation algorithm. Since various combinations were possible depending on the input variable and the output variable, it was necessary to find the optimal combination through the trial-and-error method. For such an optimal combination, it is necessary to define the network structure scenario for setting the number of layers and nodes and defining hyper parameters such as optimizers, activation functions, and dropouts (Cavallo et al., 2013). This study adopted a network structure scenario with three hidden layers considering data characteristics. Dropout is a regularization penalty to avoid overfitting. It was set to reduce prediction errors caused by overfitting. In this study, making an allowance for the amount of training data, dropout was set to 0 and 0.2 and simulated. The ReLu (Rectified Linear Unit) function was utilized as the activation function, a method of adjusting the weight of each node for optimal learning. The ReLu function allows the input value to change when the input value is greater than 0 or less than 0. It was established to resolve the problem of gradient loss of the existing Sigmoid function (Krizhevsky et al., 2012). The Adaptive Moment Estimation (Adam) method as accepted as the optimizer (Krizhevsky et al., 2012). Optimizer is used for speed and stability of learning. The Adam Method is a widely assumed algorithm since its development in 2015 (Kingma and Ba, 2015). The batch was defined as 5 as a data group designation for efficient learning and the number of epochs was designated as 1,000 for the number of learning (Bae and Yoo, 2018; Ryu et al., 2018).

### 3.3 Development of the DNN model

Table 3 shows MAE and RMSE values according to the network structure and dropout. Amongst outcomes, the model with the minimum MAE and RMSE was adopted as the final structure. As the number of hidden layer nodes increased, the MAE and RMSE values fluctuated slightly. However, the number of hidden layer nodes was minimized at 25-25-25. When the dropout was 0, MAE and RMSE values were commonly lesser than when the dropout was 0.2. It could be realized that when the number of hidden layer nodes was 25-25-25 and the dropout was 0.0, both MAE and RMSE had minimum values. Consequently, in the final structure, the number of nodes was 25-25-25 and the dropout was 0. Table 4 demonstrations the network structure and hyper parameter configuration of the optimization model.

Table 3. Training results

| Network Structure Scenario | Dropout (0) | | Dropout (0.2) | |
|---|---|---|---|---|
| | MAE | RMSE | MAE | RMSE |
| 5-5-5 | 0.521 | 0.484 | 0.521 | 0.484 |
| 10-10-10 | 0.498 | 0.468 | 0.524 | 0.484 |
| 15-15-15 | 0.521 | 0.484 | 0.523 | 0.487 |
| 20-20-20 | 0.522 | 0.484 | 0.521 | 0.484 |
| 25-25-25 | 0.476 | 0.461 | 0.521 | 0.484 |
| 30-30-30 | 0.521 | 0.484 | 0.521 | 0.484 |
| 35-35-35 | 0.521 | 0.484 | 0.522 | 0.484 |
| 40-40-40 | 0.521 | 0.484 | 0.521 | 0.484 |
| 50-50-50 | 0.521 | 0.484 | 0.522 | 0.484 |

Table 4. Network structure and hyper parameter formation of the final model

| Category | Configuration | Feature |
|---|---|---|
| Network structure | Number of Hidden Layer | 3 |
| | Node | 25-25-25 |
| Hyper-parameter | Dropout | 0.0 |
| | Activation Function | ReLu (Rectified Linear Unit) |
| | Optimizer | Adam (Adaptive Moment Estimation) |
| | Epoch | 1000 |
| | Batch Size | 5 |

### 3.4 The robustness validation of the final DNN model

An MRA (Multiple Regression Analysis) model was added for systematic validation of the final DNN model. MAE and RMSE values of these two models were compared. The MRA method is widely adopted as an essential method for numerical prediction models (Kim et al., 2021). Table 5 displays validation results of these models. Results of the DNN model showed MAE of 0.531 and RMSE of 0.480 with the verification set of data. For the test set of data, results showed MAE of 0.452 and RMSE of 0.435. There was no significant difference in MAE or RMSE between results with the test set of data and those with the verification set of data since the overfitting problem of the final model could be overlooked. In addition, the MRA model showed an MAE of 0.533 and a RMSE of 0.484. Equating outcomes of the DNN model and the MRA model, it was found that the DNN model had meaningfully minor prediction error rates of 15.2% MAE and 10.12% RMSE than the MRA model.

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Table 5. Results with the validation set and test set of data

| | Validation Set | | Test Set | |
|---|---|---|---|---|
| | MAE | RMSE | MAE | RMSE |
| DNN | 0.531 | 0.480 | 0.452 | 0.435 |
| MRA | - | - | 0.533 | 0.484 |
| DNN/MRA (%) | | | -15.20% | -10.12% |

## 4 Stage II: Cost-Benefit analysis of natural disaster risk reduction projects

This section examines economic effects through cost-benefit analysis of natural disaster risk reduction projects to reduce losses from natural disasters. To gather data, among natural disaster risk reduction projects carried out by the South Korean government, information on disaster risk reservoir maintenance projects completed in 2009-2019 was collected from the Public Data Portal (data.go.kr) managed by the South Korean government to collect and provide public data created or acquired by public institutions in one place. The system was established in 2011 to provide public data in the form of file data, visualization, and open API (Application Programming Interface) (Closs et al., 2014).

Management of a disaster risk reservoir is a part of the disaster prevention project. According to the Special Act on the Disaster Risk Reduction Project and Relocation Measures, the purpose of disaster prevention measures necessary for improving the disaster risk area is for fundamental prevention and permanent recovery of disasters. The disaster prevention project was started in 1998 when the Disaster Response Division of the Ministry of Government Administration and Home Affairs discovered disaster-prone facilities and areas with risk of human casualties and provided government funds for the maintenance of natural disaster risk areas for systematic management and prompt resolution of disaster risk factors (Lee, 2017). Disaster prevention projects include natural disaster risk improvement districts, disaster risk reservoirs, steep slope collapse risk areas, small rivers, and rainwater storage facilities (Kim et al., 2019). In this paper, a cost-benefit analysis was conducted for the natural disaster reduction project by comparing losses from storm and flood insurance before and after the disaster risk reservoir maintenance project. During the study period of 2009-2019, 474 reservoirs were designated as disaster risk reservoirs and 290 maintenance projects were initiated. Among them, a total of 12 areas were flooded before and after the completion of the disaster risk reservoir maintenance project. Table 6 shows the loss rate and maximum precipitation at the time of flooding before and after completion of the maintenance projects in these 12 areas. Data about the loss amounts from storm and flood insurance were obtained from KIDI. Precipitation data were collected from KMA and the maximum daily precipitation at the time of the flooding was used. Insured loss was expressed as a rate of the incurred loss divided by the accrued premium. The loss rate before the maintenance project was 34.32% on average, while that after the maintenance project was completed was 5.9% on average, showing a sharp decrease of 82.8% on average. However, when data of precipitation as the main cause of flooding

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accidents during flood damage were compared, the average precipitation was 331 mm/day before the maintenance project and 215 mm/day after the maintenance project. It could be seen that the amount of precipitation was decreased by 35% when flood damage occurred after the maintenance project. The sharp decrease in the loss rate after the maintenance project could be due to the effect of the maintenance project. It could also be attributed to a relatively small amount of precipitation compared to that before the maintenance project. Therefore, it is difficult to conclude that the decreased loss rate is due to the effect of reducing storm and flood damage caused by the maintenance project.

Table 6. Comparison of loss rate and precipitation before and after maintenance projects in flooded regions

| No | Region | Loss rate | | Precipitation (mm/day) | |
|---|---|---|---|---|---|
| | | Before | After | Before | After |
| 1 | Yongin City | 47.40% | 20.60% | 425 | 188 |
| 2 | Nonsan City | 30.10% | 0.80% | 334 | 306 |
| 3 | Wanju-gun | 40.70% | 3.40% | 364 | 142 |
| 4 | Gangjin-gun | 76.30% | 0.40% | 235 | 166 |
| 5 | Sejong City | 7.30% | 4.90% | 257 | 223 |
| 6 | Muan-gun | 25.80% | 2.00% | 285 | 192 |
| 7 | Hampyeong-gun | 23.80% | 10.30% | 301 | 230 |
| 8 | Gyeongju City | 33.10% | 1.20% | 488 | 280 |
| 9 | Changwon City | 10.60% | 10.70% | 300 | 266 |
| 10 | Namhae City | 22.10% | 8.50% | 324 | 231 |
| 11 | Naju City | 53.90% | 5.10% | 330 | 106 |
| 12 | Goheung-gun | 40.70% | 3.00% | 325 | 249 |
| | Average | 34.32% | 5.9% | 331 | 215 |
| | After/Before (%) | | 82.8% | | 35.0% |

Therefore, cost-benefit analysis was conducted to analyze the economic effect. Equal-payment-series present-worth factor was used for cost-benefit analysis. Equal-payment-series present-worth factor, assuming an annual loss rate i, is a coefficient used to find the present value corresponding to annual equivalent loss A for the next n years. Eq. (1) presents a widely used concept in economic analysis (Park and Sharp, 2021):

$$P = \frac{A[(1+i)^n - 1)]}{i(1+i)^n} \quad (1)$$

Where:

P: Present value

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A: Annual loss amount

I: Loss rate

n: Year

The initial cost of each maintenance project was collected through The Public Data Portal and the average cost of the maintenance project was calculated. For the loss rate, the average loss rate of the loss area was used. For the annual loss amount, the average annual loss for the study period (2009-2019) was used as seen in table 7. However, it was assumed that no additional costs incurred due to the maintenance project. Figure 1 shows calculation results before and after the maintenance project. As can be seen from Figure 1, the loss amount becomes smaller after 8 years due to investment through the maintenance project.

Table 7. Summary of input

| Input | Before | After |
|---|---|---|
| Initial cost | - | 22.088* |
| Loss rate | 0.343 | 0.059 |
| Annual loss amount | 0.371* | 0.006* |

* Billion KRW

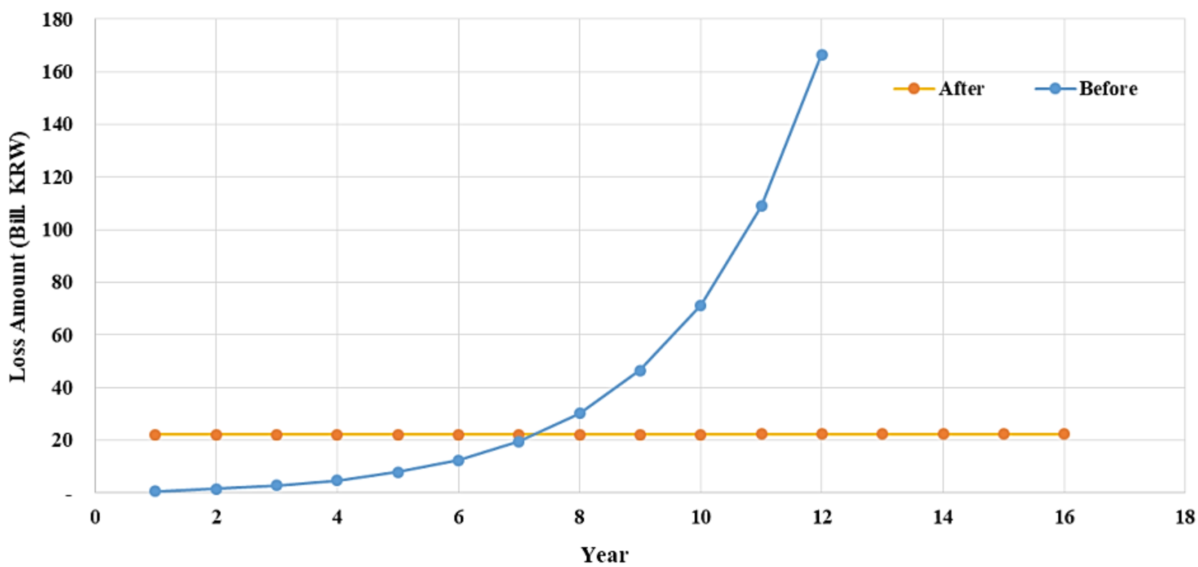


Figure 1. Comparison of losses before and after the maintenance project.

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## 5 Discussion

In Stage I, this study developed a model for predicting economic losses due to natural disasters using the DNN algorithm among deep learning algorithms. For model development, insurance company's storm and flood damage insurance loss records were used to collect economic losses caused by actual natural disasters. After developing a DNN algorithm model and training it with collected data, the model was validated by comparing different models. In addition, network scenarios and hyper-parameters were found using the trial-and-error method to derive the optimal model. The DNN model was 15.2% less in the MAE and 10.12% less in the RMSE than the MRA model. As shown in prediction results, the non-parametric model DNN was more proper than the parametric model MRA model for the economic loss analysis of natural disasters with non-linear characteristics. These results also indicate that the DNN model has higher reliability than other models in identifying financial losses due to natural disasters. Due to the nature of natural disasters, the loss is very diverse. Thus, the prediction error value can be very large. It can be seen that the DNN model reflects this diversity of natural disaster losses well. By using the development model and the methodology described in this study, natural disaster risk managers will be able to predict the financial loss cost of natural disasters or develop an optimal deep learning prediction model according to user conditions. It can also be used as a reference when developing systems or models for predicting natural disaster losses in a public or private sector. Based on this sophisticated economic loss prediction, it will be possible to make decisions for active risk reduction investment. Such investment can strengthen natural disaster risk management and reduce the amount of risk, ultimately reducing the economic loss caused by natural disasters. For example, it will be possible to calculate the amount of economic loss in an area expected to be flooded in advance and establish a preventive strategy for loss measures and appropriate facility investment according to the expected loss amount. Moreover, such loss forecasting can help prepare financial guidelines such as emergency reserves and budgeting. It can also be used to prepare budget guidelines according to the calculated expected loss and manage business continuity. In addition, according to established financial guidelines, it will be helpful for strategies to avoid and transfer financial losses through insurance coverage or special purchases suitable for expected losses. These activities can ultimately reduce the risk of financial loss due to natural disasters. Nevertheless, this study has some limitations. First, owing to the limited data set, it was problematic to accumulate different data sets. Additional research in the future is needed to parallel and prove loss records in other countries or regions. In addition, further research is required to increase the amount of available data and upgrade the model through the introduction of additional variables to more precisely predict losses from natural disasters using deep learning algorithms.

In Stage II, a methodology was proposed to quantify the effectiveness of natural disaster risk reduction projects using cost-benefit analysis. Among natural disaster risk reduction projects were implemented in South Korea, information was collected and analyzed for the disaster risk reservoir maintenance project where flood damage occurred before and after completion. To analyze benefits and costs, this study collected and analyzed the loss rate and precipitation from wind and flood damage before and after the maintenance project in the target area and judged the efficiency of the maintenance project. As a result of CBA

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analysis, in the short term, the loss after the maintenance project was greater than that before the maintenance project. However, this was reversed from 8 years after the maintenance project and the loss amount before the maintenance project was larger than that after the maintenance project. Although it is difficult to expect profits from the maintenance project in the short term, it can be seen that the maintenance project is economically beneficial in the long term (8 years or more). Results and methodology of this study will be helpful for decision making of natural disaster management policy and natural disaster risk reduction project investment. Evaluating the effectiveness of risk reduction through this analysis will lead to drastic investment, which will ultimately reduce the amount of natural disaster risk. However, the study period was relatively short and cases that could be analyzed were limited because all study subjects were from South Korea. In addition, it was assumed that the inflation rate is identical during the study period. Therefore, it is necessary to conduct additional analyses considering various locations venerable to natural disasters in other countries and more realistic financial loss values using a net present value concept.

## 6 Conclusion

Due to increasing threats to life and property from natural disasters, a variety of risk mitigation activities are being carried out extensively to reduce these threats. Economic analysis of natural disaster risk mitigation effects is becoming increasingly important due to limited public budget and economic feasibility. Therefore, in this study, a framework for developing a natural disaster loss prediction model based on a deep learning algorithm for predicting natural disaster losses was presented and a methodology for quantifying the effect of natural disaster reduction through cost-benefit analysis was presented as a case study. A DNN model for natural disaster loss prediction was developed and verified. The developed model learned and generalized the loss amount of natural disaster risk indicator facilities (building type, wind speed, total rainfall, and peak ground acceleration) and wind and flood insurance. By evaluating learning performances of 18 different DNN alternatives using RMSE and MAE values as representative evaluation indicators of deep learning algorithms, 25-25-25 hidden layers with dropouts of 0.0 structure was selected as the optimal learning model. The robustness of the developed model was technically validated by comparing RMSE and MAE values of conventional multiple regression analysis methods. Validation results confirmed that the non-parametric DNN model was powerful for predicting non-linear characteristics of losses caused by natural disasters. This study offers a holistic analytical modeling framework for the prediction of natural disaster losses utilizing deep learning algorithms.

The cost-benefit analysis was conducted on the disaster risk reservoir maintenance project that occurred before and after the completion of the flood damage. As the result, it was difficult to expect profits from the maintenance business in the short term. However, in the long term (more than 8 years), it was found that the maintenance business was economically profitable. Results and methodology of this study could be used as a guideline for decision-making of natural disaster management policies and investment in natural disaster risk reduction projects. This study an also be used as a reference for application to other types of loss. The suggested methodology can also be used to support the current knowledge framework.

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**Code and data availability.**

The data presented in this research are available from the corresponding author by reasonable request.

**Author contributions.**

**J.-M.**: contributed to the conceptualization; methodology; data curation; investigation; project administration; resources; supervision; and the writing, reviewing, and editing of the manuscript. **S.-G**: contributed to data curation, investigation, resources, and reviewing and editing the manuscript. **H.**: contributed to investigation; the reviewing the manuscript. **J.**: contributed to the methodology, software, validation, and reviewing and editing the manuscript.

**Competing interests.**

The authors declare that they have no conflictof interest.

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