



1 A Strategic Framework for Natural Disaster-Induced Cost Risk 2 Analysis and Mitigation: A Two-Stage Approach Using Deep 3 Learning and Cost-Benefit Analysis

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

29 *Keywords:* Natural disaster, mitigation, deep learning,
Artificial Intelligence,



30 **1 Introduction**

31 **1.1 Natural disaster and risk**

32 The frequency and intensity of extreme weather events due to climate change are rapidly increasing, causing various damages.
33 These damages are expected to affect extreme weather events in the short term, with various long-term effects such as sea
34 level rise and disease spread. Examples of extreme weather events include flooding, drought, heavy rain, tropical cyclone, heat
35 waves, and cold waves. These extreme weather events are rapidly increasing losses associated with their increases in frequency
36 and intensity. Increases of these losses are causing many economic losses worldwide. For example, Western European
37 countries such as France, Germany, and Switzerland were hit by three consecutive tropical cyclones (e.g., Anatol, Lothar, and
38 Martin) in 1999, resulting in a loss of 13 billion euros (Ulbrich et al., 1999). Typhoon Haiyan, which hit the Philippines and
39 China of South Asia in 2013, was one of Category 5 Super Typhoons, was the most extreme tropical cyclone recorded on land.
40 The typhoon's life-threatening wind and rain were enough to smash properties. South Asian countries adjacent to the typhoon
41 track inflicted about \$300 billion in damage (Kim et al., 2019). Hurricane Katrina, which hit the southeastern United States in
42 2005, caused the most damage in American history. Hurricane Katrina was a Category 5 tropical cyclone that had caused the
43 US Gulf Coast city to have \$180 billion in direct and indirect damage due to substantial rain and robust winds (Blake et al.,
44 2007). In the United States in 2017, three powerful hurricanes (Harvey, Maria, and Irma) caused a total damage of about \$293
45 billion, with Harvey causing \$125 billion in damage, Maria causing \$90 billion, and Irma \$77.6 billion (USNHC, 2018).

46
47 Moreover, over the past century, the severity and frequency of natural disasters worldwide have increased. Climate anomalies
48 have also increased. The Intergovernmental Panel on Climate Change (The Fifth Assessment Report, 2014) has already warned
49 of an increase in global average temperature, average sea level escalation, heating, and acidification. In many countries, severe
50 weather events such as typhoons and heavy rains and changing patterns of meteorological disasters have already increased the
51 loss of many lives and property. These damages are expected to accelerate in the future (Kim et al., 2020).

52
53 Therefore, lives and property worldwide are threatened by natural disasters. Such threats will increase. To reduce these threats,
54 numerous non-governmental organizations and countries are investing a lot of time, budget, and manpower to mitigate risks
55 from natural disasters. Mitigation of risks can reduce the loss by decreasing vulnerability or by decreasing the frequency and
56 severity of causal factors (Rose et al., 2007). For risk mitigation, the execution of financial resources should be carried out
57 quickly and extensively. In practice, the efficiency and amounts of financial resources should be considered due to limited
58 resources. Hence, it is important to grasp the amount of risk and the effect of risk reduction at the same time to achieve the
59 ultimate reduction and mitigation of risk through an efficient use of limited resources. In other words, it is essential for risk
60 mitigation against potential risks by predicting the exact amount of risk, which aims to make an active investment to reduce
61 the predicted risk, and to find out the economic effect of the risk reduction. Consequently, as part of a case study on risk
62 mitigation costs, this study developed a strategic framework by developing a natural disaster damage prediction model using



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

65

66 1.2 Natural disaster loss quantification

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

77

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

85

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

94



Benefit-Cost-Ratio


95 **1.3 Cost-benefit analysis of natural disaster risk mitigation**

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

100

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

111

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



128 2 Research objectives and methods

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

135

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

- 140 1) To collect data on loss caused by natural disasters, this study collected data on claim payout for storm and flood
141 damage insurance from the Korea Insurance Development Institute (KIDI) over the past 11 years between 2009 and
142 2019.
- 143 2) This study obtained natural disaster risk indicators based on the collected data.
- 144 3) A model of deep learning algorithm was developed using Python 3.7, Keras, and Scikit-Learn libraries. The model
145 was trained, tested, and validated using the collected data.
- 146 4) A multiple regression model was independently developed using IBM Statistical Package for the Social Sciences
147 (SPSS) version 23 for model validation.
- 148 5) The root mean squared error and mean absolute error values of the deep learning algorithm model and the multiple
149 regression analysis model were estimated and paralleled, respectively.

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

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



161 **3 Stage I: Development of a natural disaster loss prediction model**

162 **3.1 Data collection**

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

174
 175 The cost of loss due to natural disasters was divided by the total net premiums to calculate the ratio and then log-transformed.
 176 In addition, natural disaster risk indicators affecting insurance loss due to natural disasters were collected. For natural disaster
 177 risk indicators, building type, wind speed, total rainfall, and peak ground acceleration were selected as variables through past
 178 literature studies (Kim et al., 2017, 2019; Kim et al., 2020; Kim et al., 2021). A description of variables is presented in Table
 179 1. Building types were set as dummy variables that consist of residential buildings and greenhouses. Wind speed and the
 180 maximum value of rainfalls were collected from the Korea Meteorological Administration (KMA). Peak ground accelerations
 181 were collected from the National Oceanic and Atmospheric Administration (NOAA). Descriptive statistics of variables are
 182 displayed in Table 2.

183 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 (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)	✓

184



Please add distribution diagrams, and PDF

185

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

186

187 3.2 Modelling deep neural networks

188 A deep learning algorithm is a neural network with many layers and various structures in general. Its use in research and
189 industry for prediction and recognition has spread rapidly, proving its effectiveness (Kim et al., 2021). Deep learning
190 algorithms are also widely used for regression analysis and type classification as a machine learning technique (Ajayi et al.,
191 2019). Deep learning models have the same training framework as other types of neural networks. However, they can train
192 large data sets more effectively with multiple hidden layers (Bae et al., 2021). Deep learning algorithms can be divided into
193 deep neural network (DNN), generative adversarial network (GAN), recurrent neural network (RNN), convolutional neural
194 network (CNN), and auto encoder (AE) according to their structure and processing method (Kim et al., 2021). Especially,
195 DNN is used for cataloguing and prediction in various engineering and academic fields (Krizhevsky et al., 2012; Toya and
196 Skidmore, 2007). Moreover, DNNs can be applied to train and model complex nonlinear relationships due to their multi-
197 layered structures. Thus, in this study, a DNN model was accepted considering nonlinearity of collected loss data. ✓

198

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



205

206 The collected loss data were pre-processed using a z-score normalization method to adjust the unit and quantity of the data.
207 The pre-processed completed input data were divided into a training set, a verification set, and a test set of data. The training
208 set of data were used for learning of the DNN algorithm. The verification set of data were used to judge whether training was
209 optimal and the test set of data were used to verify whether the developed model was finally trained for the purpose. In this
210 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
211 set of data. Then 30% of training data were utilized as verification data.

212

213 The DNN model selected the optimal combination through a trial-and-error method since the DNN model could update the
214 weights of neural network nodes with a backpropagation algorithm. Since various combinations were possible depending on
215 the input variable and the output variable, it was necessary to find the optimal combination through the trial-and-error method.
216 For such an optimal combination, it is necessary to define the network structure scenario for setting the number of layers and
217 nodes and defining hyper parameters such as optimizers, activation functions, and dropouts (Cavallo et al., 2013). This study
218 adopted a network structure scenario with three hidden layers considering data characteristics. Dropout is a regularization
219 penalty to avoid overfitting. It was set to reduce prediction errors caused by overfitting. In this study, making an allowance for
220 the amount of training data, dropout was set to 0 and 0.2 and simulated. The ReLu (Rectified Linear Unit) function was utilized
221 as the activation function, a method of adjusting the weight of each node for optimal learning. The ReLu function allows the
222 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
223 loss of the existing Sigmoid function (Krizhevsky et al., 2012). The Adaptive Moment Estimation (Adam) method as accepted
224 as the optimizer (Krizhevsky et al., 2012). Optimizer is used for speed and stability of learning. The Adam Method is a widely
225 assumed algorithm since its development in 2015 (Kingma and Ba, 2015). The batch was defined as 5 as a data group
226 designation for efficient learning and the number of epochs was designated as 1,000 for the number of learning (Bae and Yoo,
227 2018; Ryu et al., 2018).

228

229 3.3 Development of the DNN model

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

237

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

238

239

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

240

241 3.4 The robustness validation of the final DNN model

242 An MRA (Multiple Regression Analysis) model was added for systematic validation of the final DNN model. MAE and RMSE
 243 values of these two models were compared. The MRA method is widely adopted as an essential method for numerical
 244 prediction models (Kim et al., 2021). Table 5 displays validation results of these models. Results of the DNN model showed
 245 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
 246 RMSE of 0.435. There was no significant difference in MAE or RMSE between results with the test set of data and those with
 247 the verification set of data since the overfitting problem of the final model could be overlooked. In addition, the MRA model
 248 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
 249 that the DNN model had meaningfully minor prediction error rates of 15.2% MAE and 10.12% RMSE than the MRA model.



Please add Figures with distribution of actual out model.

250 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%

251 **4 Stage II: Cost-Benefit analysis of natural disaster risk reduction projects**

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

258
259 Management of a disaster risk reservoir is a part of the disaster prevention project. According to the Special Act on the Disaster
260 Risk Reduction Project and Relocation Measures, the purpose of disaster prevention measures necessary for improving the
261 disaster risk area is for fundamental prevention and permanent recovery of disasters. The disaster prevention project was started
262 in 1998 when the Disaster Response Division of the Ministry of Government Administration and Home Affairs discovered
263 disaster-prone facilities and areas with risk of human casualties and provided government funds for the maintenance of natural
264 disaster risk areas for systematic management and prompt resolution of disaster risk factors (Lee, 2017). ✓ Disaster prevention
265 projects include natural disaster risk improvement districts, disaster risk reservoirs, steep slope collapse risk areas, small rivers,
266 and rainwater storage facilities (Kim et al., 2019). In this paper, a cost-benefit analysis was conducted for the natural disaster
267 reduction project by comparing losses from storm and flood insurance before and after the disaster risk reservoir maintenance
268 project. During the study period of 2009-2019, 474 reservoirs were designated as disaster risk reservoirs and 290 maintenance
269 projects were initiated. Among them, a total of 12 areas were flooded before and after the completion of the disaster risk
270 reservoir maintenance project. Table 6 shows the loss rate and maximum precipitation at the time of flooding before and after
271 completion of the maintenance projects in these 12 areas. Data about the loss amounts from storm and flood insurance were
272 obtained from KIDI. Precipitation data were collected from KMA and the maximum daily precipitation at the time of the
273 flooding was used. Insured loss was expressed as a rate of the incurred loss divided by the accrued premium. The loss rate
274 before the maintenance project was 34.32% on average, while that after the maintenance project was completed was 5.9% on
275 average, showing a sharp decrease of 82.8% on average. However, when data of precipitation as the main cause of flooding



but also due to decreases in precipitation in fall.

276 accidents during flood damage were compared, the average precipitation was 331 mm/day before the maintenance project and
 277 215 mm/day after the maintenance project. It could be seen that the amount of precipitation was decreased by 35% when flood
 278 damage occurred after the maintenance project. The sharp decrease in the loss rate after the maintenance project could be due
 279 to the effect of the maintenance project. It could also be attributed to a relatively small amount of precipitation compared to
 280 that before the maintenance project. Therefore, it is difficult to conclude that the decreased loss rate is due to the effect of
 281 reducing storm and flood damage caused by the maintenance project.

282 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%

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

287
$$P = \frac{A[(1+i)^n - 1]}{i(1+i)^n} \quad (1)$$

B.C.R ?

289 Where:

290 P: Present value



291 A: Annual loss amount

292 I: Loss rate

293 n: Year

294

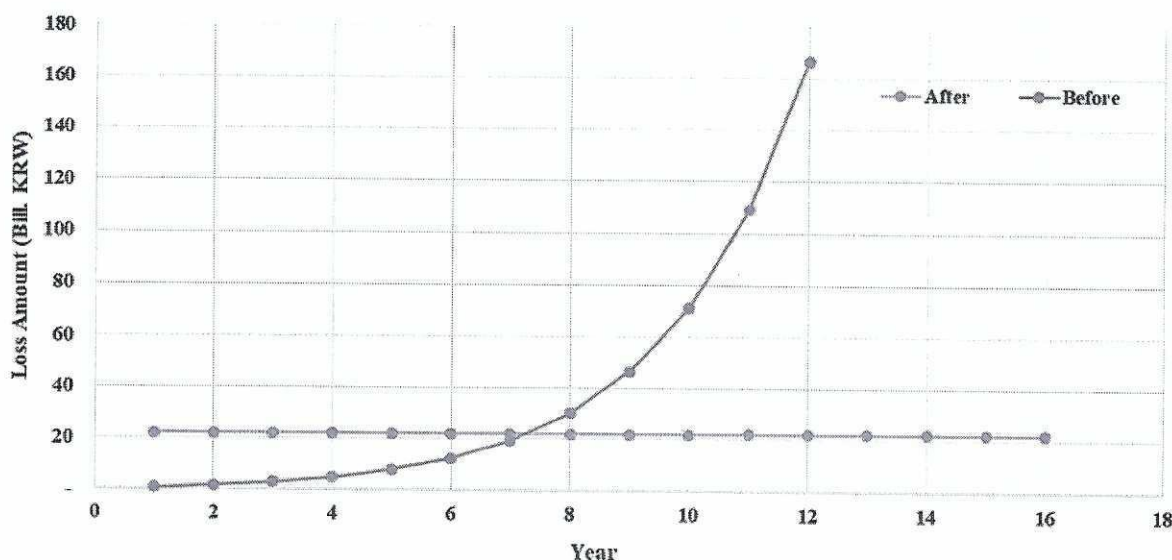
295 The initial cost of each maintenance project was collected through The Public Data Portal and the average cost of the
 296 maintenance project was calculated. For the loss rate, the average loss rate of the loss area was used. For the annual loss amount,
 297 the average annual loss for the study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

301

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*

302 * Billion KRW



303

304

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



305 5 Discussion

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

332
333 In Stage II, a methodology was proposed to quantify the effectiveness of natural disaster risk reduction projects using cost-
334 benefit analysis. Among natural disaster risk reduction projects were implemented in South Korea, information was collected
335 and analyzed for the disaster risk reservoir maintenance project where flood damage occurred before and after completion. To
336 analyze benefits and costs, this study collected and analyzed the loss rate and precipitation from wind and flood damage before
337 and after the maintenance project in the target area and judged the efficiency of the maintenance project. As a result of CBA



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

348 6 Conclusion

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

363
364 The cost-benefit analysis was conducted on the disaster risk reservoir maintenance project that occurred before and after the
365 completion of the flood damage. As the result, it was difficult to expect profits from the maintenance business in the short
366 term. However, in the long term (more than 8 years), it was found that the maintenance business was economically profitable.
367 Results and methodology of this study could be used as a guideline for decision-making of natural disaster management
368 policies and investment in natural disaster risk reduction projects. This study ^{can} also be used as a reference for application to
369 other types of loss. The suggested methodology can also be used to support the current knowledge framework.



370

371 **Code and data availability.**

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

373 **Author contributions.**

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

378 **Competing interests.**

379 The authors declare that they have no conflict of interest.

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