Response to the **Reviewer #2**' comments concerning **NHESS-2021-294**

We sincerely thank the Reviewer 2 for the time in effort on reviewing our manuscript with many insightful comments. We believe that we have addressed each of the comments carefully and properly, and we will revise the manuscript, by fully reflecting those in the next stage of the revised manuscript submission. We hope that the changes listed below are acceptable for publication. Please note that the line numbers addressed in this letter indicates the numbers shown in the manuscript submitted initially as we are not allowed to upload the revised manuscript itself yet.

General Comment: Gradual increases in the frequency and severity of natural disasters increase loss risk of human life and property. It is important to estimate the damages caused by the disaster before such events occurs. The authors attempted to develop a strategic evaluation framework and analyzed the natural disaster risk mitigation strategies by DNN methods with data of insured loss amounts between 2009 to 2019. The ideas is scientific and topic is suitable for NHESS.

Thank you for positively viewing our research ideas, with very insightful comments listed below. We appreciate it.

Comment 1: The quality of the data determines whether the analysis results are scientific. The authors carry out the research with data on claim payout for storm and flood damage insurance from the Korea Insurance Development Institute. But how many pieces? What information in the data? The author only gave the data name and resources. It is necessary to describe the data information in detail.

We do believe that certain KIDI data/information sets not used in this study are beyond scope of this study. Indeed, Table 1 describes the information of data, while Table 2 includes the sample size, 458 samples obtained from KIDK for this study.

Nevertheless, to address the comment, we have added explanation about the data information, which reads between Line 172 and Line 173:

"*The collected data information includes the total loss amounts, the total net premiums, building types, and location profiles, which is publicly available.*"

In addition, to provide the data information in detail, we have added new figures of distributions of training data sets and learning output (i.e., loss ratio), as follows:

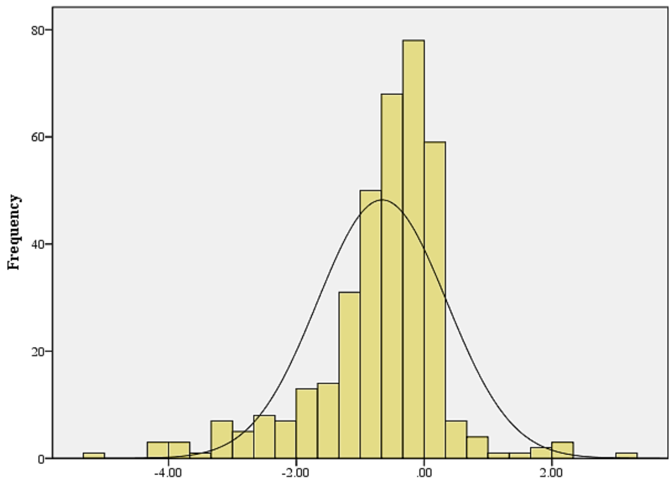
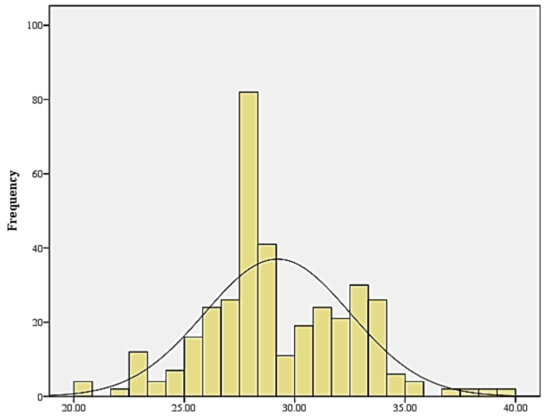
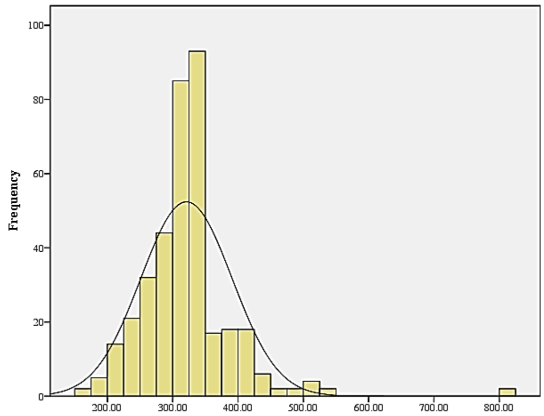


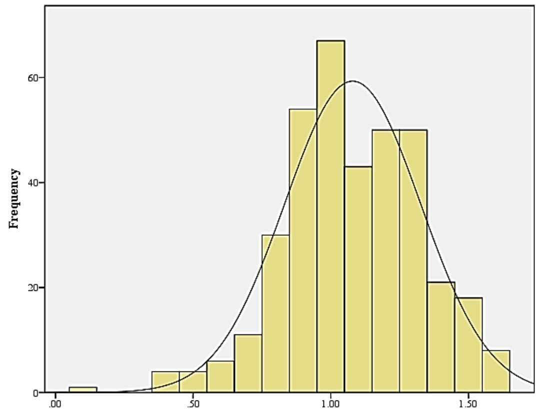
Figure 2. Distribution of insurance loss ratio record



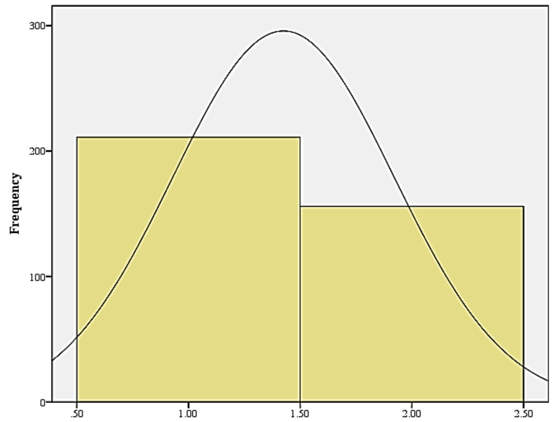
(a) Wind speed (m/s)



(b) Rainfall (mm/day)



(c) Peak ground acceleration (g)



(d) Building type (1: residential; 2: greenhouse)

Figure 3. Distributions of indicators to learn the loss ratios

Comment 2: The data collected are claim payout for storm and flood damage. But the selected disaster factors include wind speed and Peak Ground Acceleration. What is the reason? What is the relationship between them?

Indeed, in the manuscript, we have already addressed various cases of natural disasters that can be covered by insurance (Line 168 – Line 171), which reads "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)."

Given the information, we have selected "wind speeds", "rainfall" and "*peak ground acceleration as the indicator for the loss amount caused by earthquakes*" by affected building types. To support our justification, we have already cited proven previous studies (Line 178: Kim et al., 2017; Kim et al., 2020; Kim et al., 2021) in the main text body.

We hope that it clarifies.

Comment 3: It is an interesting attempt to use DNN to predict disaster loss. The authors just trained the model and compared it with MRA model. I think it is import to analyze it in detail and use it in resent disaster cases.

Indeed, the main purpose of developing the DNN model as the strategic implementation process (SIP 1) in the proposed framework is to introduce more powerful method that can improve the predictability of natural disaster-triggered financial loss values, comparing with a traditional method like MRA, not about its applicability of the model to other recent cases. The result of SIP 1 confirms that the predictability of DNN is more accurate and reliable than traditional multiple regression analysis.

We hope that this is acceptable and reasonable. Thank you.

Comment 4: The authors describe two stages in their work. Stage I is to create a predictive model based on a deep learning algorithm with data on claim payout for storm and flood damage insurance. Stage II is to analyzed the cost-benefit with data on natural disaster risk reduction projects. There seems to be no logical relationship between the two. What is the relationship between the two stages? The authors should describe it clearly.

Thank you for this comment. To provide the intention of this study and the core phases of the methodology clearly, we have replaced "stages (sequential process)" with "strategic implementation process (SIP)".

In other words, the revised SIPs are not sequentially related, but these represent the implementation processes in the proposed strategic framework. Accordingly, we have revised the abstract and the relevant main text body, while adding the research framework diagram.

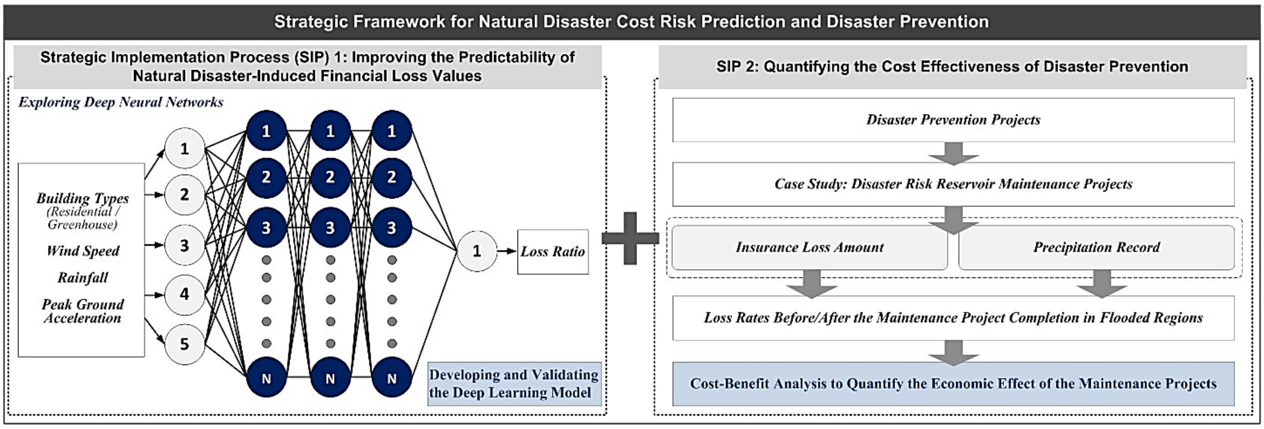


Figure 1. Research framework

The Revised Abstract:

"*Given trends in more frequent and severe natural disaster events, developing effective mitigation strategies is crucial to reduce negative economic impacts on built assets, due to the limited budget for rehabilitation. To address this need, this study aims to develop a strategic framework for natural disaster risk mitigation, highlighting two different strategic implementation processes (SIPs). SIP-1 is intended to improve the predictability of natural disaster-triggered financial loss model. To this end, SIP-1 develops a deep neural networks (DNN)-driven learning model that learns insurance loss amounts to generalize loss ratios, associated with major indicators including rainfall, wind, and ground acceleration. SIP-2 underlines the risk mitigation strategy at the project level, by adopting a cost-benefit analysis method that quantifies the cost effectiveness of disaster prevention projects. To demonstrate SIP-2, a case study of disaster risk reservoir projects in South Korea was adopted. The validated result of SIP-1 confirmed that the predictability of DNN is more accurate and reliable than traditional multiple regression analysis, while SIP-2 revealed that maintenance projects are economically more beneficial in the long-term as the loss amount becomes smaller after 8 years, coupled with the investment in the projects. The proposed framework is unique as it provides a* *combinational approach to mitigating cost risk impacts of natural disasters at both financial loss and project levels. This study is its first kind and will help practitioners quantify the loss from natural disasters, while allowing them to evaluate the cost effectiveness of risk reduction projects through a holistic approach.*"

Comment 5: Sections about the methods and results should be revised. The authors mixes methods and results together in Section 3 and Section 4, which are nor clearly presented.

Thank you for the comment. Indeed, the content structure of research has been highlighted by each SIP. In turn, we have addressed each SIP in each of the sections. Given the intentions, we do believe that the section 3 (SIP 1) has been structured clearly, from the data collection (section 3.1) to the model validation (section 3.4). Nevertheless, to clarify the main purpose of SIP 1, we have revised the corresponding section title to "*3 Improving the predictability of natural disaster-induced financial loss values using deep learning*".

we do agree with the reviewer's comment on the section 4. Hence, we have re-structured and re-written the section 4 to clearly present the SIP 2, as follows:

"*4 SIP 2: Quantifying the cost effectiveness of natural disaster risk reduction projects using cost-benefit analysis*

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). Given the significance of disaster prevention projects, SIP 2 examines economic effects through cost-benefit analysis of natural disaster risk reduction projects to reduce losses from natural disasters. To demonstrate SIP 2, 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.

4.1 Data collection and investigation of historical record
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). 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.

<Table 6 here>

4.2 Cost-benefit analysis and results of natural disaster risk reduction projects
As seen in Table 6, when data of precipitation as the main cause of flooding 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 not only the effect of maintenance project, but also decreased rainfalls. In turn, 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.

To analyze the cost effectiveness of the maintenance projects in flood regions, a cost-benefit analysis method using an equal-payment-series present-worth factor was adopted. The 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 & Sharp, 2021):

<Equation (1) here>

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. Figure 1 (now "Figure 5" in the revised manuscript) 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…."