Response to the **Reviewer #1**' comments concerning **NHESS-2021-294**

We sincerely thank the Reviewer 1 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: … The paper deserves minor revisions as follows:

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

Comment 1: The title of the manuscript is too long, please consider shorter title such as: "Natural Disaster-Mitigation Using Deep Learning and Cost-Benefit Analysis".

Thank you for the suggestion. We have revised the title properly:

"*Strategic Framework for Natural Disaster Risk Mitigation Using Deep Learning and Cost-Benefit Analysis*"

Comment 2: The abstract does not reflect the novelty of the methodology. Please consider revision: stress the validity of findings and efficiency of the framework.

Thank you for this comment. To clarify the validity of findings and efficiency of the framework, the abstract has been re-written fully. In addition, to eliminate a logical fallacy of two aspects (i.e., stages 1 and 2) raised by the Reviewer 2, the abstract and the relevant main text body have been revised, especially the revised abstract reads:

"*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 3: The literature review may be extended to applications of Deep Learning to risk assessment – Please review and consider the following literature: (Khosravi et al. 2020; Zhang et al. 2022; Yi et al. 2020; Al Najar et al. 2021; Moishin et al. 2021; Shane Crawford et al. 2020; Sugiyarto and Rasjava 2020; Kim et al. 2021).

Thank you for the constructive suggestion. Accordingly, the statement of deep learning applications for risk assessment has been added in the section 1.2, by reviewing the recommended articles as follows:

Al Najar, M., Thoumyre, G., Bergsma, E. W., Almar, R., Benshila, R., and Wilson, D. G. (2021). Satellite derived bathymetry using deep learning. *Machine Learning*, 1-24.

Khosravi, K., Panahi, M., Golkarian, A., Keesstra, S. D., Saco, P. M., Bui, D. T., and Lee, S. (2020). Convolutional neural network approach for spatial prediction of flood hazard at national scale of Iran. *Journal of Hydrology*, *591*, 125552.

Kim, J., Yum, S., Son, S., Son, K., and Bae, J. (2021). Modeling Deep Neural Networks to Learn Maintenance and Repair Costs of Educational Facilities. *Buildings*, *11*(4), 165.

Moishin, M., Deo, R. C., Prasad, R., Raj, N., and Abdulla, S. (2021). Designing deep-based learning flood forecast model with ConvLSTM hybrid algorithm. *IEEE Access*, *9*, 50982-50993.

Rasjava, A. R. I., Sugiyarto, A. W., Kurniasari, Y., and Ramadhan, S. Y. (2020, April). Detection of Rice Plants Diseases Using Convolutional Neural Network (CNN). In *Proceeding International Conference on Science and Engineering* (Vol. 3, pp. 393-396).

Shane Crawford, P., Hainen, A. M., Graettinger, A. J., van de Lindt, J. W., and Powell, L. (2020). Discrete-outcome analysis of tornado damage following the 2011 Tuscaloosa, Alabama, tornado. *Natural Hazards Review*, *21*(4), 04020040.

Yi, Y. and Zhang, W. (2020). A new deep-learning-based approach for earthquake-triggered landslide detection from single-temporal RapidEye satellite imagery. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 6166-6176.

Zhang, Y., Shi, X., Zhang, H., Cao, Y., and Terzija, V. (2022). Review on deep learning applications in frequency analysis and control of modern power system. *International Journal of Electrical Power & Energy Systems*, *136*, 107744.

Accordingly, the extended review of literature reads (from Line 91):

"*Given the increasing demand, many research efforts on applying deep learning techniques for risk assessment were made recently (Al Najar et al. 2021; Khosravi et al. 2020; Kim et al. 2021; Moishin et al. 2021; Shane Crawford et al. 2020; Sugiyarto and Rasjava 2020; Yi et al. 2020; Zhang et al. 2022). Especially, for improved natural disaster risk assessment and mitigation, neural networks have been widely used for deep learning in various ways (Khosravi et al. 2020; Moishin et al. 2021; Shane Crawford et al. 2020; Yi et al. 2020).*

Some researchers developed deep learning models to predict flood events (Khosravi et al. 2020; Moishin et al. 2021). Khosravi et al. (2020) developed a flood susceptibility map using convolutional neural networks (CNN). More specifically, 769 historical flood locations in Iran were trained and tested based on amounts of soil moisture, slopes, curvatures, altitudes, rainfalls, geology, land use and vegetation, distances from roads and rivers. In addition, a hybrid deep learning algorithm integrating the merits of CNN and long short-term memory (LSTM) networks was built to manage flood risks by predicting future flood events, by training and testing daily rainfall data obtained from 11 sites in Fiji between 1990 and 2019 (Moishin et al. 2021).

Other previous studies focused on post-disaster detection caused by landslides or tornados, which uses remote sensed data collected from satellites for deep learning (Al Najar et al. 2021; Shane Crawford et al. 2020; Yi et al. 2020). Shane Crawford et al. (2020) adopted CNN to classify damages of 15,945 buildings affected by the 2011 Tuscaloosa tornado in Alabama. To this end, the authors used satellited-driven images of trees as the damage classification indicator to estimate wind speeds. In addition, satellite images were *embraced into the CNN-driven deep learning process to detect earthquake-induced landslides in China (Yi et al. 2020). More recently, Al Najar et al. (2021) estimated accurately ocean depths simulating remote sensed images using a deep learning technique, which overcomes drawbacks of traditional bathymetry measurement activities to track the physical evolution of coastal areas against any potential natural disasters or extreme storm events. Previous studies reviewed reveal consistently that deep learning techniques can overcome shortcomings of existing methods and thus to provide more accurate and reliable decision-support models for risk assessment and risk-informed mitigation strategies.*

In addition to applications of deep learning for location detection or event prediction-focused, as stated earlier, it is important to quantify negative economic impacts caused by natural disasters. Given the importance of economic damage aspects, Kim et al. (2021) applied a deep learning technique as a cost-effective and risk-informed facilities management solution. In detail, the authors generalized maintenance and repair costs of educational facilities in Canada, using deep neural networks that learn sets of maintenance and repair records, asset values, natural hazards such as tornados, lightening, hails, floods, and storms. In this sense, this study proposed a deep learning modeling framework to predict financial losses caused by natural disasters."

Comment 4: Please add a research framework diagram, emphasize the core phases of the methodology.

Thank you for this comment. To provide the intention of this study and the core phases of the methodology clearly, the research framework diagram has been added.

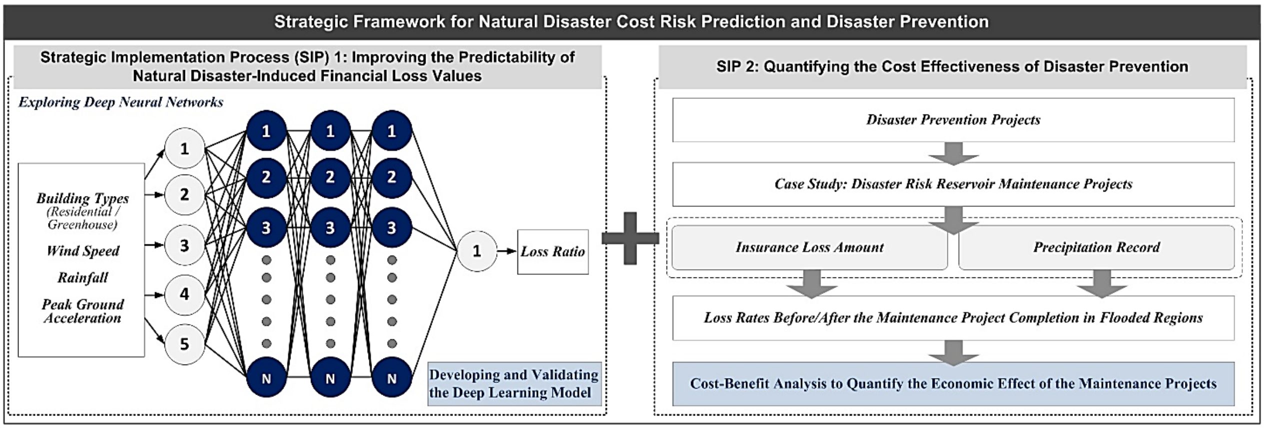


Figure 1. Research framework

As stated earlier by responding to comment 1, we have highlighted the main purpose of each of the SIPs.

Thank you.

Comment 5: The training phase of the DNN must be significantly improved: please provide figures with distributions of the core variables, please provide distribution figures of the training data (Loss ratio, building type, maximum wind speed, rainfall and PGA), the MRA model and the DNN output. This is essential to for legibility and scientific soundness.

Thank you for the comments. We have provided figures of distributions of learning output (i.e., loss ratio) and indicators, as follows:

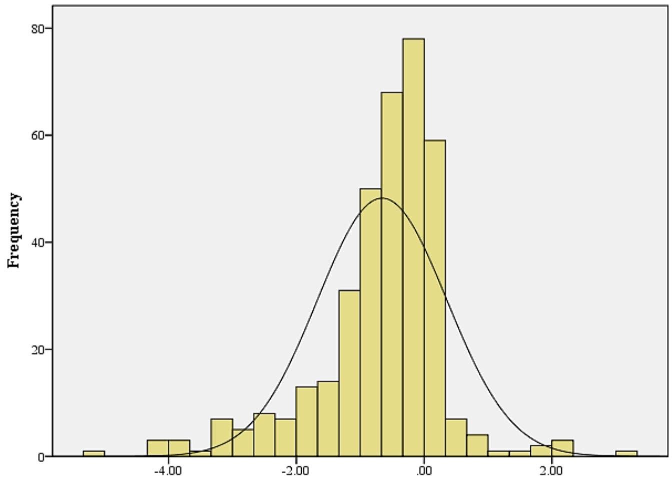
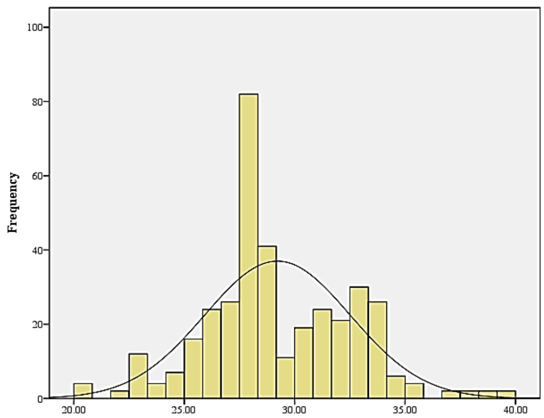
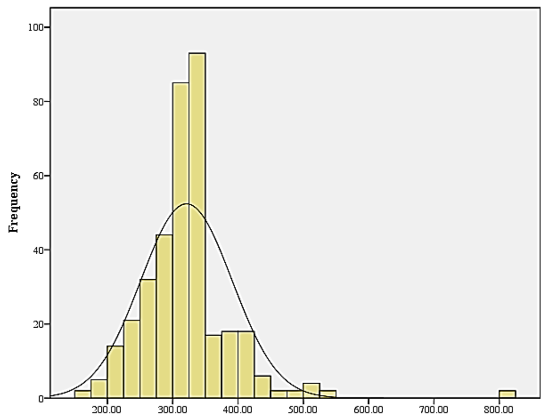


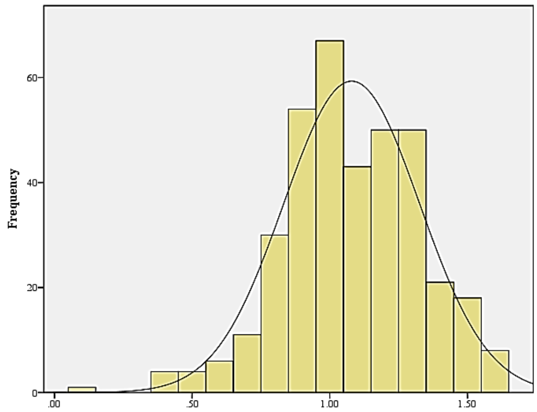
Figure 2. Distribution of insurance loss ratio record



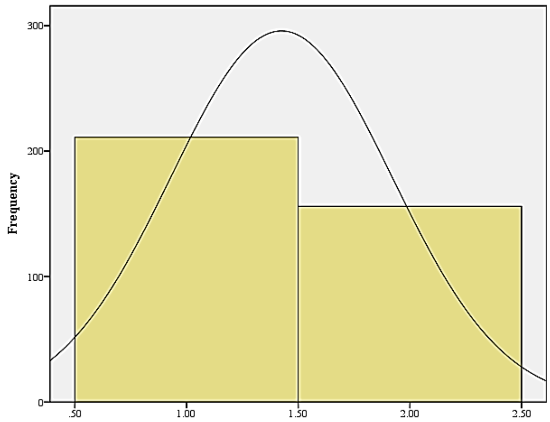
(a) Wind speed (m/s)



(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

On the other hand, when it comes to MRA-to-DNN output comparison, the main purpose of SIP 1 was 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 focused on the achievement of predicted values themselves. In this sense, we have provided Table 5, which would be effective enough to show the comparison results of the predictability scientifically, with the error values.

Alternately, to provide more clear result of the final DNN, we have provided the network architecture graphically, along with Table 4.

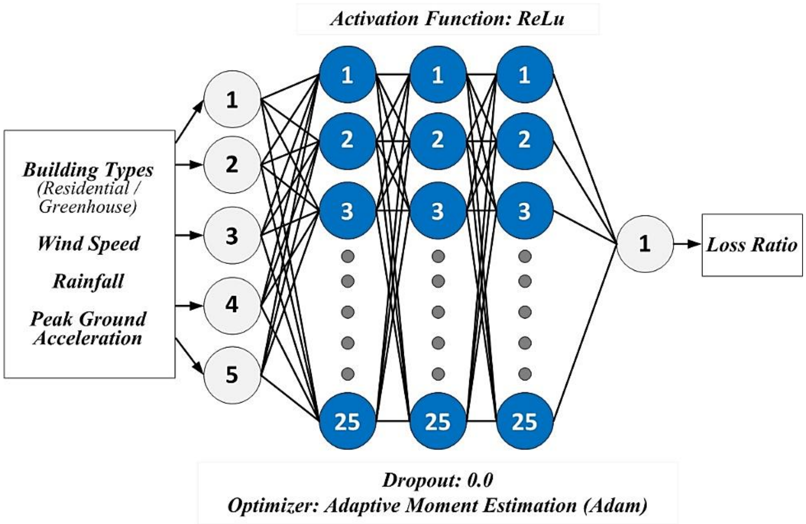


Figure 4. Final model of deep neural networks

We hope that this is acceptable for your consideration.

Comment 6: Please add keyworks.

Thank you for pointing this out. We have addressed this comment, by adding keywords as follows:

Keywords: Natural disaster; risk mitigation strategy; economic damage; deep learning; cost-benefit analysis

Comment 7: Please see further remarks and corrections in the attached file.

Overall, thank you for your insight review. We would appreciate it. Accordingly, we have corrected minor errors as well.

- Line 81: The duplicated word, "earthquakes" has been eliminated.
- Line 82: The transition "In addition" has been replaced with "Furthermore."
- The terms between "cost-benefit" vs "benefit-cost": We have made the use of term consistently, with "cost-benefit" throughout the paper.
- Line 125: "disaster reduction" has been replaced with "disaster risk reduction."
- Line 278 – Line 279 corrected to "due to not only the effect of maintenance project, but also decreased rainfalls."
- Line 297: The typo has been corrected (i.e., table 7 → Table 7).
- Line 300 corrected to "projects."
- Line 350: "to reduce these threats" has been eliminated.
- Line 368: The typo has been corrected (i.e., an → can).