**<u>AC: Authors’ Response to Reviewer</u>**

Respected Anonymous Reviewer,

The authors of this manuscript appreciate your invaluable suggestions and comments for further improvement of our manuscript. All comments are very useful. We have read all comments carefully and revised our manuscript according to your suggestions (changes are presented in red color in the manuscript). Detailed responses to the comments are presented below.

1. Most of the Introduction describes the development of deep learning methods, lacking the necessity of developing the review of water-related disasters.

   The Introduction section has been re-written to reveal the need for the research. The last paragraph has been structured to indicate the need, scope and aim of the study – Line 91-94.

   In summary, the authors discovered that developed countries have been researching and adopting more data-driven approaches (specifically deep learning techniques) in mitigating disaster risk through computer vision, flood segmentation tasks, prediction, clustering etc. Only few research papers and reports emanated from developing countries. This created a research need to study the reasons for such a slow adoption, trends, and drivers of deep learning (DL). Therefore, the first paragraph in the Introduction section addressed evolution of AI; second paragraph focused on recent big data availability, while the last paragraph presented the research approach. We briefly discussed the UNDP’s Human Development Index to guide our choice of countries ranked as developing countries. Thank you.

2. The selection process of final reviewed articles (Figure 2) is not clear. I am confused about the “records excluded (n=16)” and “Abstract relevance”.

   Thank you for raising this comment. After we had submitted the article, we discovered that we did not include the reason for excluding the sixteen (16) articles in our PRISMA schema. The criterion for removal was data source. After the first filtering, we checked study area reported in all ninety-eight (98) articles and removed 16 papers that used hydrological datasets from developed countries (countries with Human Development Index > 0.80 according to UNDP), because we focused on articles from developing countries. We have updated the reason for exclusion in the new draft – Figure 2.

   Abstract Relevance: Then, the authors retrieved and studied eighty-two (82) articles fully. We identified and excluded thirty-eight (38) articles that do not address water-induced disaster but managed to form part of our query output from search databases. We have edited the “Abstract Relevance” reason for clarity in the new manuscript draft – Figure 2. Thank you for this wonderful observation.

3. I suggest to provide the final search keywords with “OR” and “AND”. For example, (“flood” OR “drought”) AND (“deep learning”).

   Thank you for this excellent suggestion. We have included the query from Web of Science as requested **- Line 118 - 110**
   *(TS=("Deep learning" AND "developing countries" OR "recurrent neural network" OR "water-related disaster" OR "hydrology" OR "streamflow prediction" OR "water level prediction" OR "disaster" OR "flood forecasting " OR "flood" OR "drought" OR "landslide" OR "hurricane", "storm surge" OR "tsunami))*

4. Figure 9 is not clear. **– Figure 9**

   Figure 9 shows the chart of models used in our reviewed articles. We have edited the figure caption and the axis title for more clarity.

   We identified and counted different deep learning models (not machine learning algorithms) that were used in the reviewed articles to portray how the number of times these models had been used. For example, LSTM and hybrids include LSTM with other DL model ensembles, were applied in thirty-two (32) articles of the reviewed papers. This output is only limited to the scope of our work and our methodology. This was sufficient to track country location and to subsequently categorize the country into developing and developed. Thank you.

5. After the inspection of Table 2-5, all the studies are carried out in recent 4 years, excluding Kumar et al. (2004), Pereira Filho & Dos Santos (2006), and Chen et al. (2015).

   Thank you for your wonderful observation. Although deep learning research was first implemented and published by Alexey and Lapa in 1967 (Ivakhnenko et al., 1967), it evolved and gained momentum in water resources and environmental studies only in recent years as a subfield of machine learning. The early implementation was done by developed countries until lately when developing countries decided to adopt the technique. Developed countries had been benefiting immensely from this paradigm shift. For the scope of our work, the HDI criterion helped to track specific research outputs from developing countries and publication dates were reported as stated. Evidently, a larger percentage of all publications in the academic space in the last three decades had been published in developed countries. Our approach might not be exhaustive and there might be very few articles that might miss the designed query but summarily, we believe that this research presents a vivid representation of the trend and an important point of reference for future research.

6. Section 4.2: the effect of data size in different disaster maybe different. For example, we cannot provide a larger number of samples in landslide field.

   The authors of this manuscript clearly agree with the reviewer that effect of data size of different disasters may be different. Similarly, the authors had established the same fact that due to the large spatial scope of the study (developing countries) and uncertainties due to heterogeneity, the effect of data size on model performance does not show a clear relationship. Based on the results of the study, it is hard to validate the general findings of the Power Law: "more data, better performance" as established by (Alom et al., 2019; van Essen et al., 2015; Yetilmezsoy et al., 2011) . This raises the question of how much data is enough to obtain optimal modeling results? Although the concept of autocorrelation can select appropriate input variables for better prediction, but the DL field is still evolving and more interesting areas are yet to be explored. In our manuscript, we identified hyperparameter tuning and efficient data cleaning as better factors for improving model performance.
   We have edited the previous manuscript for more clarity – Section 4.2 Line 274 - 279

7. Section 4.3.2: In my opinion, if we include the landslide hazard in the review, there are lost of papers that using deep leaning methods in this field.

   If the query search is extended to water-related disaster globally or in developed countries, landslide studies and other pertinent disaster studies can be captured. We showed this when we compared publication trend in developing countries and global trend – Figures 5 and 6. Thank you.

8. This manuscript misses many related papers, such as:

- Wang, Y., Fang, Z., Hong, H., Peng, L., 2020. Flood susceptibility mapping using convolutional neural network frameworks. Journal of Hydrology, 582, 124482

- Fang, Z., Wang, Y., Peng, L., Hong, H., 2021. Predicting flood susceptibility using LSTM neural networks. Journal of Hydrology, 594, 125734.
- Xu, S., Niu, R., 2018. Displacement prediction of Baijiabao landslide based on empirical mode decomposition and long short-term memory neural network in Three Gorges area, China. Computers & Geosciences, 111, 87-96.
- Van Dao, Dong, et al. "A spatially explicit deep learning neural network model for the prediction of landslide susceptibility." Catena 188 (2020): 104451.
- Shahabi, Himan, et al. "Flash flood susceptibility mapping using a novel deep learning model based on deep belief network, back propagation and genetic algorithm." Geoscience Frontiers 12.3 (2021): 101100.

Although the first two papers were studied during the literature review part of the work to provide some background knowledge for the study – Line 61, we agree that they should form part of the main reviewed articles because the studies utilized DL models, data sources were from developing countries, and they fall within our research scope. Therefore, we have extensively reviewed all recommended articles based on our methodology. We have effected changes in the updated manuscript. Thank you.

9. I cannot find any review of flood mapping in this manuscript.

We reviewed flood mapping articles and summarized in Table 2 (Afan et al., 2022; Kanth et al., 2022; Khosravi et al., 2020; Xu et al., 2021). Based on your recommendation, we added more flood mapping articles that met the scope of our study (Fang et al., 2021; Shahabi et al., 2021; Wang et al., 2020).

Thank you for the excellent addition.

10. Section 4.3: it would be better to provide some comparison and summary work for these studies, not only describe each paper standalone.

Thank you for your constructive comments. We analyzed the reviewed papers by discussing the main applications and DL models that the authors reported in their study. We summarized and grouped the applications into: (i) flood mapping, forecasting and rainfall prediction; (ii) landslide susceptibility mapping; (iii) snow avalanche prevention; (iv) land subsidence and drought.

**New edits**

6.74 billion….. and 85.43% (new update from data source) – Line 81

trends ~~in the water-induced disaster~~ in (word repetition) - Line 94

Hussain and Mahmud (citation edited) - Line 154

Removed Figure 4: Publication count by country (repetition of Figure 3) - Line 176

Removed "Water management" (not necessary) – Section 4.3.4. Thank you.

## References


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