RC 1: (posted on 3rd April 2025)

This study evaluates flood risk in the Ganga River Basin using the Analytical Hierarchy Process (AHP) approach, considering risk as a function of hazard, exposure, and vulnerability. A key aspect of the study is the use of night-time lights as a proxy for flood exposure, which is presented as a novel contribution. However, I find the study lacking in terms of scientific innovation, methodological advancements, and practical applications. My primary concern is the reliance on proxy variables for flood hazard assessment rather than actual hazard data. Detailed comments are as follows:

- *Lack of novelty:* AHP is a widely used method in flood risk assessments across various regions, including India. A simple literature search reveals numerous similar studies applying AHP in flood risk analysis…The present study primarily replicates an established approach with minor variations in proxy variables, offering limited scientific advancement:

  https://doi.org/10.1007/s11600-018-0233-z

  https://doi.org/10.1007/s10661-022-10111-x

  https://doi.org/10.1007/s11069-018-3392-y

  https://doi.org/10.1007/s11069-019-03737-7

  https://doi.org/10.5194/hess-21-2219-2017

  https://doi.org/10.1186/s40677-016-0044-y

  https://doi.org/10.1007/s12524-008-0034-y

  We thank the reviewer for pointing to relevant literature that indeed confirms the wide applicability and acceptance of the AHP method in flood risk assessments. While AHP has been employed extensively in similar contexts **the primary novelty and importance of our study lies not in the methodological framework itself, but in the integration of a dynamic exposure dataset—specifically, night-time lights (NTL)**. We do agree with the reviewer that we should have explained this better in the introduction. The purpose of employing AHP in this study was intentional, as it is a tested and interpretable method. Rather than replacing the methodology, our goal was to **strengthen it with contemporary data inputs** that can improve its responsiveness and relevance. This aligns with scientific practice where methodological frameworks are enhanced through novel inputs or contextual applications. The review recognises the NTL work is a novel contribution, and we believe this integration represents an important advancement in data-driven flood risk assessment for several key reasons:

  1. **NTL as an Exposure Proxy:** While previous studies (e.g., Gosh and Kar, 2018 and Danumah et al., 2016) rely on static or census-based demographic and infrastructure indicators, our study uniquely demonstrates the use of night-time light intensity as a spatially and temporally continuous proxy for human exposure and urbanisation. NTL has not to date been incorporated within flood risk literature and offers high-resolution insights into evolving exposure patterns.
  2. **Temporal Scope and Resolution:** The use of annual NTL data over a 10-year period introduces a longitudinal dimension to exposure analysis, capturing growth of human presence dynamics that are often missed in single-year assessments, which is often the case in using the

census-based population dataset. This enhances the capacity of the AHP model to reflect exposure changes—an important improvement over conventional static dataset.

3. **Enhanced Decision-Making Utility:** By integrating a globally available, regularly updated dataset (NTL), the approach we present can be more easily replicated across data-scarce regions. It aligns with the goal of developing scalable, low-cost methodologies for flood risk assessment, especially relevant for rapidly urbanising regions in the Global South.

Although the core methodological approach is established, our work provides added value by operationalising the NTL dataset in a practical, geospatial, and decision-support context—an aspect that is not well addressed in the cited literature. To make this as clear as possible for readers revised the manuscript to more explicitly emphasise the contribution of the study in terms of data innovation within a validated analytical framework.

We have restructured the Introduction section, where we have addressed the above clarifications, and emphasised the importance of NTL.

Line 83-94 reads as *"The key novelty of the approach lies in using night-time lights (NTL) as a proxy for flood exposure within the basin, unlike the population data, and leveraging the temporal availability of the data. NTL data is collected from satellite-based sensors like VIIRS (Visible Infrared Imaging Radiometer Suite) which offers a dynamic, consistent, and spatially explicit view of human activity and settlement patterns. Over the past decade, NTL data have been increasingly used to monitor urban expansion, economic activity, and disaster impacts (Andries et al., 2023; Román et al., 2018; Wang et al., 2018). The NTL data can reflect the real-time distribution of human activities at a large scale and with better temporal frequency, compared to traditional statistics and census data (Fang et al., 2021). More recently, studies have explored its application to examine human exposure and presence near rivers, including those associated with floods (Aggarwal et al., 2024; Ceola et al., 2014). Elshorbagy (2017) prepared flood exposure map of Canada is developed using a land-use map and the satellite-based nightlight luminosity data as two exposure parameters. The use of annual NTL data for flood risk assessment over a 10-year period introduces a longitudinal dimension to exposure analysis, capturing growth of human presence dynamics that are often missed in single-year assessments, which is often the case in using the census-based dataset."*

Line 151 – 154: "*The purpose of employing AHP in this study is to strengthen the framework with contemporary data inputs that can improve its responsiveness and relevance. This aligns with scientific practice where methodological frameworks are enhanced through novel inputs or contextual applications. This enhances the capacity of the AHP model to reflect exposure changes—an important improvement over conventional static dataset*."

- *Use of proxy variables for hazard assessment:* The study estimates flood hazard using proxy variables derived from DEM, rainfall, and geomorphological data, rather than employing actual flood hazard data. More robust approaches, such as using satellite-based flood observations (e.g., Sentinel data) or hydrodynamic flood models, would provide a more accurate representation of flood hazard. Recent studies have successfully integrated observed flood data into multi-criteria decision-making (MCDM) models.

We acknowledge that actual flood observations—especially those derived from remote sensing or simulation—can offer valuable insights into the spatial extent of flooding event. While satellite datasets were not used as primary inputs for hazard modelling in our study, however, we did use Sentinel imagery and other remote sensing products for visual inspection and cross-referencing, especially in areas with a known history of inundation. This was done to qualitatively validate the areas identified as high hazard zones through potential -based analysis. However, the choice of proxy variables in our study was based on specific considerations, as outlined below:

1. Limitations of Satellite-based flood observation: Sentinel-1 SAR data, while effective for flood detection due to its cloud-penetrating capabilities, has limited temporal resolution (typically 12-day revisit period over non-European countries). This makes it challenging to capture short-duration flash flood events unless coinciding with the satellite overpass. Optical datasets (e.g., MODIS, Landsat) provide higher temporal coverage but suffer significantly from cloud cover, especially during monsoon events when flood mapping is most needed. Moreover, mapping potential (rather than past or observed) flood hazard using satellite data would require long-term archival image analysis, which becomes methodologically and computationally intensive—particularly for a large study area (approximately 860,000 km^2). Integrating multiple satellite sources to address temporal and spatial gaps would further increase the complexity and resource demands of the study, which was not feasible within the scope of this research.

2. Limitation of Hydrodynamic flood models: Hydrodynamic models require a variety of input data, including precipitation records, discharge data, and flow depth measurements, which are typically collected via rain gauges, river gauge stations, and hydrological datasets. In India, these datasets are often not readily available at the required spatial and temporal resolution for flood hazard modelling. Many regions lack publicly accessible, consistent, or high-quality rainfall and discharge data. In addition, hydrological station coverage may be sparse. The is typically managed by governmental agencies or research organizations, and accessing this information often requires formal requests or approvals. This process can be time-consuming, particularly for large geographic regions, and might involve bureaucratic delays, making it impractical within the scope and time constraints of this study.

Given the above limitations, we adopted a widely accepted approach using proxy variables (e.g., elevation, slope, drainage, rainfall) that are: Freely and readily available, relevant to flood generation processes and frequently validated in peer-reviewed flood risk assessments (e.g., AHP-based studies). While these proxies may not offer the same level of precision as hydrodynamic models, they have been effectively used in numerous flood risk assessments globally (as mentioned by the reviewer in the first comment), and they provide a reasonable alternative, especially when observed flood data is not available. These proxies offer consistent and scalable inputs for estimating flood risk, particularly in data-scarce and rapidly urbanising regions, and allow integration within the GIS-MCDM framework without compromising spatial coverage.

- *Methodological limitations and justification:* The traditional AHP model relies heavily on expert judgment, which introduces uncertainty. Recent studies have addressed this limitation by incorporating hybrid deep learning models and fuzzy AHP approaches, allowing for the integration of binary flood hazard data (e.g., flood-prone vs. non-flood-prone zones) into MCDM frameworks. Furthermore, quantitative validation and uncertainty analysis are essential to ensure confidence in results. The manuscript lacks a clear justification for the chosen methodology and does not address these recent methodological advancements.

We understand that the reviewer has two concerns- chosen methodology and recent methodological advancements related to AHP, and validation/uncertainty check.

1. **AHP as the preferred methodology for flood risk mapping and the recent advancements** – We would like to highlight the reasoning made in the earlier comment that the usage of AHP was intentional as it's a well-established method for flood risk studies. We acknowledge the fact that the AHP model depends on the expert judgment, but the parameters are chosen based on a literature review and expert judgements. The AHP method permits carrying out the analysis through assessing, integrating, additionally ranking of the various conflicting factors at a certain degree of information.

   To emphasis the chosen methodology, we have modified the text in the manuscript.

   Now, Lines 107 to 113 reads as "*Hydrodynamic Models are a subset of numerical models simulate the temporal and spatial variation of water flow and are widely used for flood forecasting and inundation mapping (Horritt & Bates, 2002). It requires a variety of input data, including precipitation records, discharge data, and flow depth measurements, which are typically collected via rain gauges, river gauge stations, and hydrological datasets. Many regions lack publicly accessible, consistent, or high-quality rainfall and discharge data. In addition, hydrological station coverage may be sparse. The data gathering can be time-consuming, particularly for large geographic regions, making it impractical within the scope and time constraints of this study.*"

   Lines 118-126 "*Given the above limitations, we adopted a multi-criteria decision-making (MCDM) approach using the Analytic Hierarchy Process (AHP), which allows for the integration of geomorphological, hydrometeorological, and socio-environmental factors. AHP was developed by Saaty (1980) is one of the widely known approaches for flood risk mapping (Sinha et al, 2008; Chakraborty and Mukhopadhyay, 2019; Ghosh and Kar, 2018; Grozavu, 2017; Huang et al., 2011; Mishra and Sinha, 2020). This approach uses pairwise comparisons to assess the extent to which one factor within the model is more important than the other, thereby producing a weighting for each factor. While we do not claim that this method is universally superior to hydrodynamic modelling, it offers a practical and intuitive framework for flood risk assessment in data-limited contexts. Empirical approaches such as MCDM have been widely used in flood studies and are considered effective when supported by robust spatial datasets and expert judgment (Teng et al., 2017).*"

   To further address the recent methodological advancements related to AHP, we have added further text to the application of AHP in integration to other methods from line 145 to line 150 – "Fuzzy AHP (*FAHP) is one of the prevailing and powerful techniques that has been used for decision-making. Fuzzy set theory is the basis for doing FAHP (Xu et al., 2023 and Aggarwal et al., 2023). Mudashiru (2022) shows that the AHP and the FAHP methods applied are sensitive to model input change. Despite these variations, the flood hazard maps generated with the same factors and model presented almost similar maps to the sensitized maps. Furthermore, hybrid AI-MCDM models are emerging that combine the interpretability of MCDA with the computational intelligence of AI, thereby enabling more robust, data-driven, and context-sensitive decision-making frameworks for water resource planning (Gacu et al., 2025).*"

   Also, the ration behind choosing AHP and not fuzzy AHP was using a new dataset in already established approach, which has been mentioned in the manuscript that the AHP is the most widely used MCDM method for flood hazard modelling.

2. **Quantitative validation and uncertainty analyses** have already been performed in the study. Validation and comparison with the impact-based data using GDIS and EMDAT has been explained in the manuscript in the section 3.7 and the results are described in the section 4.7. We have addressed the need to compare our results with an impact-based dataset, which in this case is the EMDAT and GDIS.

   As stated in the manuscript from line 679 to 682 – "*In Figure 12 we observe that the ROC-AUC curve plotted between the true positive rate (TPR) and false positive rate (FPR) has an area under the curve (AUC) value of 0.69 (or 69%), which is satisfactory – very good range as per the classification Das, 2020; Lin et al., 2019; Mukhtar et al., 2024; Roy et al., 2021; Saha and Agrawal, 2020)*". We are not sure what exactly the reviewer means "Furthermore, quantitative validation and uncertainty analysis are essential to ensure confidence in results".