Reply to the Revier 2 comments:

We would like to mention that the line numbers now mentioned in the comments are the new line numbers after revising the text

The manuscript *"Increasing Flood Risk in the Indian Ganga Basin: A Perspective from the Night-time Lights"* tackles an important issue—the escalating flood risk in the Ganga Basin—by proposing a methodology that integrates multiple geospatial datasets with NASA's Black Marble night-time lights as a proxy for human exposure using an AHP approach. While the approach and dataset integration are acceptable in principle, several conceptual and methodological issues must be addressed before the paper is suitable for publication.

Thank you for the comments and feedback on the research. Below is the reasoning for each comment as listed by the reviewer.

Major Comments

1. **Modelling Framework and Terminology**

- **Clarification of Model Types:**
  The manuscript currently confuses distinct modelling approaches. The authors refer to "physical," "numerical," and "hydrodynamic" models in ways that are inconsistent with established definitions. For example, physical models should be recognized as scaled, laboratory-based representations (e.g., flume models), while numerical models involve solving equations computationally. Hydrodynamic models, in contrast, specifically address the full dynamic wave Saint Venant equations in 1 or 2 dimensions derived from the Navier–Stokes framework in 3 dimensions. I strongly recommend that the authors clearly distinguish these models and ensure that each description is both scientifically accurate and well-referenced.

  We thank the reviewer for this insightful comment and fully acknowledge the need for precise and consistent terminology when referring to different modelling approaches. In response, we have revised the manuscript to clearly distinguish between physical, numerical, and hydrodynamic models in accordance with established definitions in the literature from line 103-117 and we very much hope this makes it clearer for readers. We stress that our own results and findings are not affected by the choice of terminology.

  "*A general overview of different techniques for mapping flood-prone areas is broadly categorised into physical, numerical and empirical approaches (Liu et al., 2024; Mukhtar et al., 2024; Teng et al., 2017). Physical Models are scaled-down laboratory representations (e.g., flume or basin models) used to study flow dynamics under controlled conditions (Heller, 2011; Hughes, 1993). Numerical Models simulate fluid flow using discretised solutions to governing equations such as the Saint Venant or Navier–Stokes equations (Teng et al., 2017). 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. Empirical Models in contrast, rely on observed historical data to identify statistical or heuristic relationships rather than simulating physical processes*

(Teng et al., 2017). These include Multi-Criteria Decision-Making (MCDM) methods, which combine expert judgment with weighted spatial factors (e.g., slope, land use, rainfall) to assess flood susceptibility, statistical models like logistic regression and frequency analysis, and machine learning models that detect complex patterns from large datasets (Mosavi et al., 2018; Rahmati et al., 2016).

".

- **Terminology Consistency:**
  The terms "flood risk," "flood susceptibility," and "flood impacts" appear to be used interchangeably without precise definitions. This lack of clarity undermines the overall conceptual framework. I urge the authors to define these terms explicitly at the beginning of the manuscript and maintain consistent usage throughout the text.

  We sincerely thank the reviewer for highlighting this important issue. We agree that consistent and precise use of terminology is critical for clarity and conceptual rigor and we agree with the reviewer that we can improve this further. In response to this comment, we have made the following revisions and clarifications:

  1. In line with the IPCC (2014) framework, we have now explicitly defined "flood risk" in the manuscript (lines 63–65) as follows: "*According to the IPCC (2014) report, flood risk is defined as the potential for adverse consequences. It is a product of hazard, exposure and vulnerability based on the common framework adopted by the United Nations*."
  2. The term "susceptibility" was originally used in the manuscript in accordance with its general meaning: "the state or fact of being likely or liable to be influenced or harmed by a particular thing" (Oxford Dictionary). However, we acknowledge that in the context of flood risk assessments, susceptibility is more appropriately associated with hazard rather than risk. To prevent confusion, we have revised the manuscript to remove or rephrase the term where necessary. For example, the phrase: "Higher FHI means higher susceptibility to floods" has been revised to "Higher FHI means higher probability of flooding."
  3. Following the IPCC, "impacts" refer to the consequences of realized risks on natural and human systems, including effects on lives, livelihoods, infrastructure, ecosystems, and more. In our study, the term "impacts" is specifically used in reference to data derived from EMDAT and GDIS, which record the actual consequences of flood events. If the reviewer's concern relates to the comparison made in Section 3.7, where modelled risk areas are validated against historical flood impact data from EMDAT, we would like to clarify that the terms are not used interchangeably in that context. Rather, we aim to assess whether areas identified as having high flood risk (i.e., areas with high hazard, exposure, and vulnerability) correspond to areas that have experienced actual flood impacts. We believe this validation step is appropriate and conceptually consistent with the definitions provided.

     We have revised the manuscript to ensure clear, consistent, and IPCC-aligned terminology throughout. We greatly appreciate the reviewer's comment, which helped improve the clarity and conceptual robustness of our work.

- **Scientific Accuracy and Data Interpretation**
- **Rainfall Versus Precipitation:**
  The manuscript contains statements suggesting that "rainfall" and "precipitation" are synonymous. However, precipitation is a broader term that includes snow, ice, and hail, while rainfall does not. This distinction is critical in the context of flood risk assessment, particularly in regions where non-rainfall

events may contribute to flooding. The authors should either revise this for accuracy or provide a strong justification for their interchangeable usage.

We thank the reviewer for highlighting this important distinction. In our study area, flooding is predominantly caused by **rainfall events**, and other forms of precipitation such as snow or hail do not significantly contribute to flood hazards. Our intention was to refer specifically to rainfall throughout the manuscript.

To maintain terminological accuracy and consistency, we have revised the manuscript to replace instances of "precipitation" with "rainfall" where appropriate. We believe this revision improves clarity and aligns the language of the manuscript more closely with the physical processes relevant to the study area.

- **Justification of Dataset Choices:**
  The choice of datasets, particularly the ASTER-GDEM and CHIRPS data, is a subject of concern. Several studies indicate that higher-resolution DEMs (e.g., those derived from Copernicus DEM) might offer more reliable vertical accuracy.
- Similarly, while CHIRPS is a robust dataset, some recent literature suggests that GPM-IMERG may provide superior performance in monsoon-dominated regions. The manuscript would benefit from a more detailed discussion on the selection of these datasets and any limitations they might introduce.
- I am also really confused by the choice of the annual nighttime lights dataset as a proxy, even when the NASA Black Marble product includes daily products (https://doi.org/10.1016/j.rse.2018.03.017) which would correspond much better to flood recovery processes (see here: https://doi.org/10.1016/j.rse.2025.114645). Would the yearly averaged product not smooth out the impacts in most areas, defeating the purpose or the proxy? Or are the authors claiming only to examine floods where no recovery was possible within a year to be able to see this impact on an annual scale? In any case, this is the main novelty of the paper apparently so I strongly recommend better defending this methodological choice and how this may influence their conclusions.

Thank you for raising these important points regarding the selection of datasets and the use of NASA's Black Marble Nighttime Lights (NTL) product.

1. On the choice of ASTER-GDEM and CHIRPS data: We acknowledge that higher-resolution DEMs such as the Copernicus DEM offer improved vertical accuracy and could enhance hazard modelling, particularly for small-scale hydrological analyses. However, in our study, we selected ASTER-GDEM at 1 arc-second (~30 m) resolution due to its compatibility with the spatial resolution of other datasets—especially the NTL dataset, which has a coarser resolution (~500 m, or 15 arc-seconds). The objective was to harmonise all layers to a common spatial resolution for weighted overlay and minimise interpolation errors during resampling. Given that our analysis focuses on regional-scale patterns across the large expanse of the Ganga Basin, the vertical resolution of ASTER-GDEM was considered sufficient for capturing broad-scale hydro-geomorphic variations.

Similarly, CHIRPS was selected for precipitation data due to its long temporal coverage, high spatiotemporal resolution (0.05°), and robust performance in data-scarce regions. While we recognise the increasing use of GPM-IMERG, comparative studies show mixed results in monsoon-dominated areas, with some favouring CHIRPS for its bias-corrected historical performance and better agreement with rain gauge data over India. Nonetheless, we acknowledge this limitation and will include a brief comparative discussion in the revised manuscript to clarify our dataset choice and its implications.

2. On the use of annual Nighttime Lights (NTL) data: We appreciate the reviewer's insight and agree that the daily NTL product has great utility in disaster response and recovery assessments. However, our study focuses on long-term flood risk assessment, not short-term flood impact or recovery dynamics. The primary goal was to quantify average annual exposure to flood risk, akin to how demographic datasets (e.g., census-based population) are used in many existing studies. For this purpose, the annual NTL product provides a consistent, smoothed estimate of human presence and economic activity over time.

While we acknowledge that daily NTL could offer finer temporal sensitivity, it is also subject to limitations such as cloud cover, moonlight interference, and post-disaster power disruptions, making it less reliable for long-term trend analyses. The yearly NTL product, by averaging over these daily variations, offers a stable proxy for human settlement patterns, particularly useful when examining multi-annual trends in exposure across a large and diverse region like the Ganga Basin.

Moreover, a key novelty of our work lies in leveraging a decade-long time series of annual NTL data to track exposure evolution—a capability not offered by static population datasets. This supports a more dynamic and spatially resolved assessment of flood risk, aligning with our study's aim to map changing flood risk patterns over time, rather than evaluate isolated flood events. This point has been highlighted in the manuscript from line 83 to 89 – "*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)*".

- **Methodological Presentation**
- **AHP Framework:**

The use of the Analytical Hierarchy Process (AHP) for integrating multiple flood risk factors is not novel even though it is widely used and acceptable in this case. However, **the manuscript would benefit from clearer descriptions of how the pairwise comparisons were conducted, how consistency was ensured, and how the resulting weights were validated**. In some instances, the paper appears to overcomplicate the presentation of these steps. A more concise explanation, supported by relevant references, would improve readability.

Thank you for your observation regarding the use of the Analytical Hierarchy Process (AHP) and its methodological clarity.

We would like to respectfully point out that the manuscript already provides a clear and structured explanation of the AHP implementation. Section 3.2 (Lines 272-275) outlines the four core stages of the AHP process: (i) parameter hierarchy construction, (ii) pairwise comparison matrix, (iii) weight normalisation, and (iv) consistency check, supported by appropriate literature (Ghosh and Kar, 2018; Mishra and Sinha, 2020; Roy et al., 2021). Unlike many studies that treat these steps in a generalised manner, we have deliberately broken down and described each phase in detail to enhance transparency and reproducibility.

After discussion with the co-authors, we believe the current level of detail is appropriate and sufficient for understanding the methodology. However, we have edited the section lightly to make sure things are as readable as possible.

- **Exposure and Vulnerability**
- While the use of night-time lights as a proxy for human exposure is interesting, the manuscript does not sufficiently differentiate exposure from vulnerability. In several sections, vulnerability data (e.g., district-level vulnerability indices) are used in contexts that suggest they represent exposure. A thorough re-examination and clear delineation of these concepts are needed.

  The definition of exposure and vulnerability is already described in the manuscript from line 69 to 74.
  - *"Exposure is defined as the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected",*
  - *"Vulnerability is defined as the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt".*

  The important aspect of this research was to identify hazard, exposure and vulnerability and differentiate between each of them in influencing the flood risk. We are not sure how the reviewer thinks that the vulnerability and exposure have been used interchangeably.

  However to highlight the indicators of vulnerability index used in the Climate Vulnerability Assessment Report produced by the Department of Science and Technology, Government of India, we have added the names of the indicators used in section 3.1 from line 242 to 248 – *"The indicators used in the report were - Percentage of population living below the poverty line (BPL), income share from natural resources, share of horticulture in agriculture, proportion of marginal and small landholdings, women's participation in the workforce, Yield variability of food grains, area under rainfed agriculture, forest area per 1000 rural population, incidences of vector- borne diseases and water-borne diseases, Area covered under centrally funded crop insurance schemes (such as Pradhan Mantri Fasal Bima Yojna (PMFBY) and Revised Weather-based Crop Insurance, Scheme (RWBCIS), implementation of Mahatma, Gandhi National Rural Employment Guarantee, Act (MGNREGA), road and rail-network, the density of healthcare workers".*

Minor Comments

- **Figure and Visual Clarity:**
  Some figures, such as the workflow diagram and flood hazard maps, are not sufficiently legible at 100% zoom. I recommend that the authors provide higher-resolution images or ensure that all text and symbols are easily readable.
  Thank you for the feedback. The figures have been revised.

- **Scale and Resolution Issues:**
  There are questions regarding the spatial and temporal resolutions used, the rainfall data are daily, aggregated to monthly scales – the aggregation method is not specified – and then kept just for the monsoon months but then is compared to annual scale night-time lights data, which does not really make sense from my point of view.

The rainfall data used in the study were originally available at a daily temporal resolution. These were aggregated to monthly totals using a summation method and then averaged over the five-month monsoon period (June to October) for each year. This period was selected because it corresponds to the primary flood season in the study area, during which most flood events occur. We have now explicitly stated the aggregation method and rationale in the revised manuscript.

However, to be precise in the manuscript, we have revised the text and added the aggregation method from line 331 to 334 – *"For rainfall analysis, we used the daily data CHIRPS raster data to prepare the monthly total rainfall. These were aggregated to monthly totals using a summation method and then averaged over the five-month monsoon period (June to October) for each year. This period was selected because it corresponds to the primary flood season in the study area, during which most flood events occur."*

Regarding the use of annual night-time lights (NTL) data, we acknowledge the temporal mismatch with the monsoon-season rainfall data. However, the NTL data in this study were not used to capture short-term flood dynamics but rather to serve as a proxy for human settlement patterns and population distribution, which are relatively stable over the course of a year. This approach is consistent with previous studies that have used NTL data as a spatial indicator of exposure or vulnerability in flood risk assessments (e.g., Ceola et al., 2014)

- **References:**
  Several assertions in the manuscript lack adequate citation. For example, claims about the effectiveness of different modelling approaches and the influence of rainfall intensity on flooding should be supported by additional literature.
  Thank you for the feedback. This has been mentioned in the previous comments, and we have tried our best now to address the different modelling approaches and influence of rainfall on flooding.

In its current form, the manuscript has several conceptual ambiguities and methodological inconsistencies that must be resolved before publication. Addressing these concerns will substantially strengthen the manuscript and enhance its contribution to the field of flood risk assessment.