Forecasting Flood Inundations in the Delta Region of a Highly Flood-Prone Tropical River Basin

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January 9, 2023

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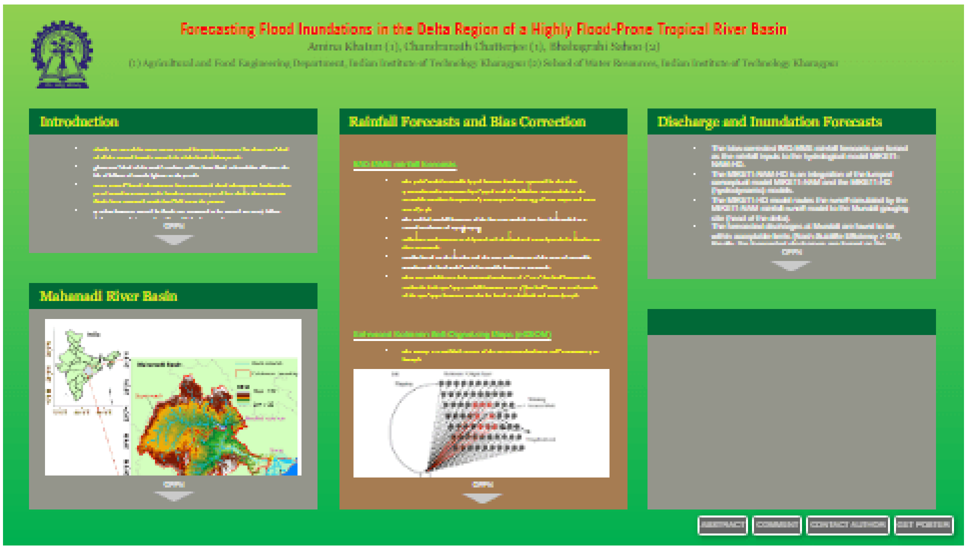

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INTRODUCTION

- Floods are one of the most severe natural disasters accounting for about one-third of all the natural hazards around the globe (Lechowska, 2018).
- About one-third of the Earth's surface suffers from flood vulnerability affecting the life of billions of people (Aksoy et al., 2016).
- Using ground-based observations from Dartmouth Flood Observatory (Brakenridge, 2018) records, a recent study (Najibi & Devineni, 2018) has shown that in tropics, floods have increased nearly four-fold since the 2000s.
- In India, damages caused by floods are estimated to be around US $54.3 billion within a span of 63 years (1953-2016) (Chandra, 2019).
- Using the same data set with 32-year (1985-2016) flood records, Halgamuge and Nirmalathas (2017) reported an increase in flood magnitude and associated damage in India.
- Nearly 40 million hectare landmass of India is flood-prone and every year nearly 8 million hectare of land is affected by floods (Ray et al., 2019).
- Thus, reliable and accurate prediction of flood magnitudes and the inundations caused by the high flooding events with sufficient lead-time is of great importance for developing early flood warning systems.

MAHANADI RIVER BASIN

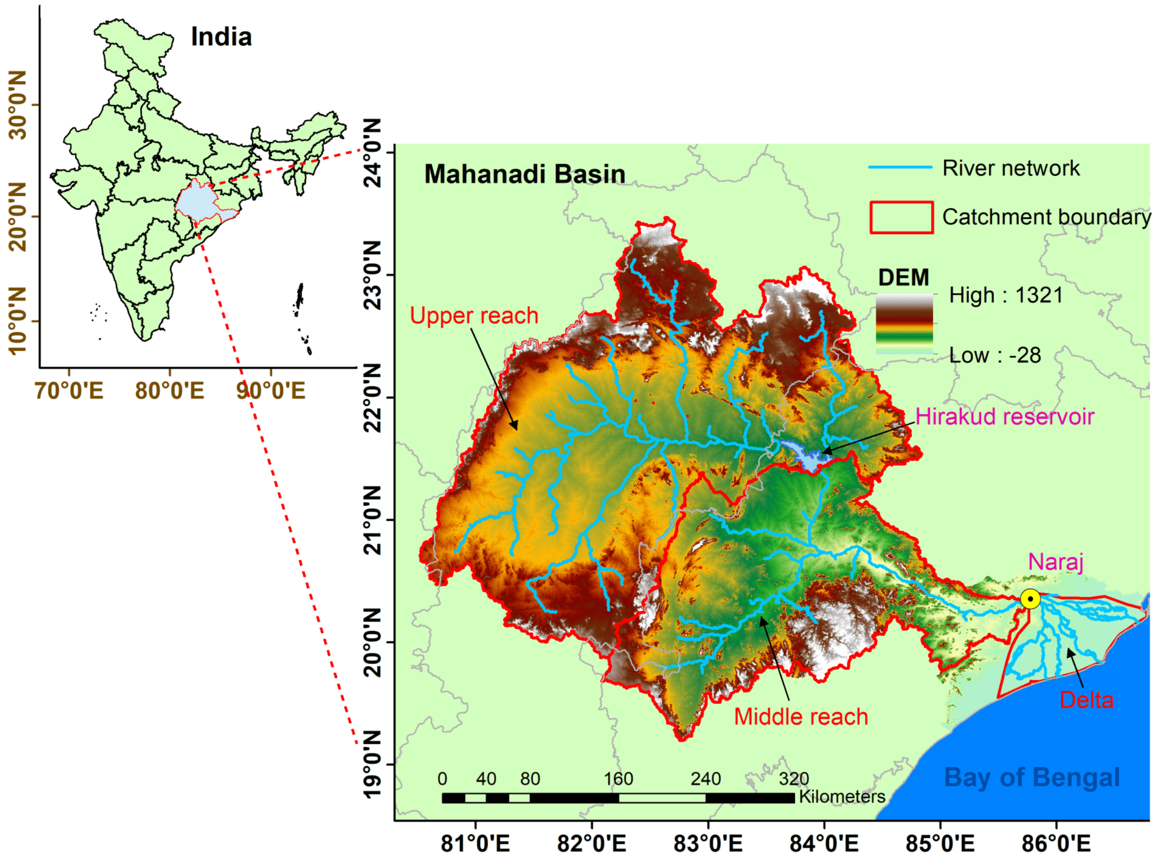


Fig. 1: The Mahanadi River basin

- The Mahanadi River basin lying in the eastern part of India has a total geographical area of 141,589 km^2.
- About 53% of the river basin lies in the state of Chhattisgarh and 46% is in Odisha, supporting ~27.4% and 4%, respectively, for irrigation and industrial purposes.
- The basin is located in the core monsoon region (18-28°N and 73-82°E) and in close proximity to the Bay of Bengal, which makes it extremely vulnerable to the tropical-cyclone-induced severe storms (Ghosh et al., 2019; Sahoo & Bhaskaran, 2018) and extreme rainfall-induced fluvial floods during the southwest monsoon (June-September) season.
- The Hirakud dam (Fig. 1) and the Naraj gauging site divides the entire basin into upper reach, middle reach and the delta region.
- The entire river basin is rainfed with about 1400 mm average annual rainfall occurring mostly (more than 90%) during the southwest monsoon (June-September).

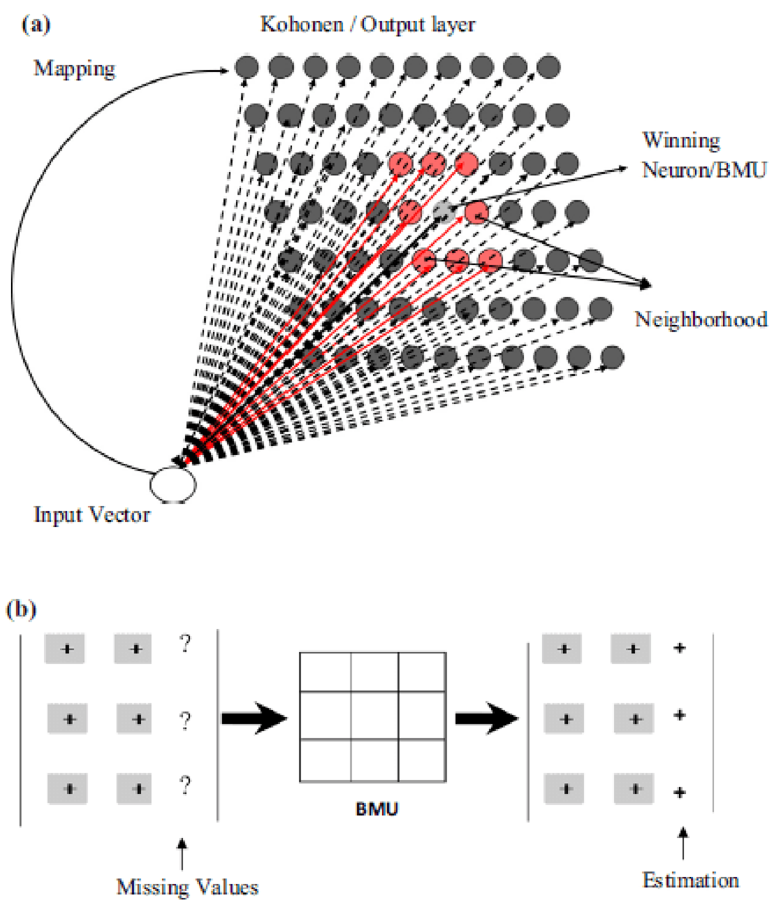
RAINFALL FORECASTS AND BIAS CORRECTION

IMD-MME rainfall forecasts

- The Multi-model ensemble (MME) forecast database prepared by the India Meteorological Department (IMD-MME) used the following NWP models as the ensemble members (NCMRWF T-254, ECMWF T-799, JMA T-959, UKMO and NCEP GFS T-382).
- The gridded rainfall forecasts of the five NWP models are first downscaled to a spatial resolution of 0.25°×0.25°.
- Following Krishnamurti et al. (2000) and Bhowmik and Durai (2008), the weights are then generated.
- Finally, based on the weights and the past performance of the suite of ensemble members, the final multi-model ensemble dataset is prepared.
- They are available at a daily temporal resolution of 1- to 5-day lead-times. In this study, the daily IMD-MME rainfall forecasts up to 2-day lead-time are used. Details of the IMD-MME forecasts can also be found in Bhowmik and Durai (2012).

Enhanced Kohonen Self-Organizing Maps (eKSOM)

- The eKSOM is a modified version of the conventional Kohonen Self-Organizing Map (KSOM).



(a) Kohonen self-organizing feature map (KSOM) and (b) Variable estimation from best matching unit (BMU) search in KSOM (Adeloye et al., 2011).

Fig. 2. Kohonen self-organizing feature map (KSOM) and (b) Variable estimation from best matching unit (BMU) search in KSOM (Source: Nanda et al., 2017).

- The basic KSOM estimator recognizes the underlying pattern in the training dataset using a specific set of vectors of the two-dimensional maps, namely, the weight or code vectors.
- These maps are defined by considering a definite number of map units or nodes or neurons (*M*). The pattern between the input and output data layers forms a matrix of N rows of d-dimensional sample vectors.

- Each map unit is expressed by a d–dimensional code vector forming a codebook of size $M \times d$ which are then initialized with small random values during the training of KSOM.
- For testing, the values of variables during the validation period are purposefully removed. A neuron with the least Euclidean distance, called the Best Matching Unit (BMU), is then searched for the testing datasets.
- The IMD-MME rainfall forecasts are bias-corrected using this eKSOM method.
- In the enhanced KSOM, the optimum number of map units for each year at each lead-time are obtained for each of the grids in the study area.
- For this, the number of map units is varied externally with a sequential increment of 10 units each time from the default value (M) up to a number below the total available data points.

DISCHARGE AT THE HEAD OF THE DELTA

- The bias-corrected IMD-MME rainfall forecasts are forced as the rainfall inputs to the hydrological model MIKE11-NAM-HD.
- The MIKE11-NAM-HD is an integration of the lumped conceptual model MIKE11-NAM and the MIKE11-HD (hydrodynamic) models.
- The forecasted discharges at Mundali are found to be within acceptable limits (Nash-Sutcliffe Efficiency > 0.5). Finally, the forecasted discharges are forced into the MIKE FLOOD model.
- The inundation extent simulated by the MIKE FLOOD model up to 2-day lead-time was found to match with the observed satellite-based inundation layer with a reasonable accuracy.

REFERENCES

- Aksoy, H., Kirca, V. S. O., Burgan, H. I., & Kellecioglu, D. (2016). Hydrological and hydraulic models for determination of flood-prone and flood inundation areas. Proceedings of the International Association of Hydrological Sciences, 373, 137-141.
- Bhowmik, S.K.R, and Durai, V.R., 2008. Multi-model ensemble forecasting of rainfall over Indian monsoon region. Atmosfera, 21(3), 225-239.
- Bhowmik, S.K.R., and Durai, V.R., 2012. Development of multimodel ensemble based district level medium range rainfall forecast system for Indian region. Journal of Earth System Science, 121(2), 273-285.
- Brakenridge GR, 2018. Global active archive of large flood events, Dartmouth Flood Observatory, University of Colorado. https://floodobservatory.colorado.edu/Archives/index.html
- Chandra, S. (2019). State wise flood damage statistics. CWC, technical report number, 3/38/2012-FFM/1067-1164. Government of India.
- Ghosh, A., Das, S., Ghosh, T., & Hazra, S. (2019). Risk of extreme events in delta environment: A case study of the Mahanadi delta. Science of the Total Environment, 664, 713-723.
- Halgamuge, M. N., & Nirmalathas, A. (2017). Analysis of large flood events: Based on flood data during 1985-2016 in Australia and India. International Journal of Disaster Risk Reduction, 24, 1-11.
- Krishnamurti, T.N., Kishtawal, C.M., Zhang, Z., LaRow, T., Bachiochi, D., Williford, E., Gadgil,S., and Surendran, S., 2000. Multimodel ensemble forecasts for weather and seasonal climate. Journal of Climate, 13(23), 4196-4216.
- Lechowska, E. (2018). What determines flood risk perception? A review of factors of flood risk perception and relations between its basic elements. Natural Hazards, 94(3), 1341-1366.
- Najibi, N., & Devineni, N. (2018). Recent trends in the frequency and duration of global floods. Earth System Dynamics, 9, 757-783.
- Nanda, T., Sahoo, B., and Chatterjee, C., 2017. Enhancing the applicability of Kohonen Self-Organizing Map (KSOM) estimator for gap-filling in hydrometeorological time series data. Journal of Hydrology, 549, 133-147.
- Ray, K., Pandey, P., Pandey, C., Dimri, A. P., & Kishore, K. (2019). On the recent floods in India. Current Science, 117(2), 204-218.
- Sahoo, B., & Bhaskaran, P. K. (2018). Multi-hazard risk assessment of coastal vulnerability from tropical cyclones - A GIS based approach for the Odisha coast. Journal of Environmental Management, 206, 1166-1178.

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ABSTRACT

Accurate discharge forecasts at the upstream locations plays a vital role in developing forecasted inundation maps for the downstream low-lying areas. The present study attempts to simulate the forecasted inundations for the 2011 flood event in the highly flood-prone delta region of an Indian River basin, the Mahanadi. The ensemble Numerical Weather Prediction (NWP) model outputs at each grid in the upstream reaches of the delta were bias corrected using enhanced Kohonen Self-Organizing Maps to prepare the rainfall inputs to an integrated hydrological model, MIKE11-NAM-HD. The simulated discharge forecasts up to 2-day lead-time at the head of the delta were used to simulate the flood inundations in the delta region using the coupled 1D-2D MIKE FLOOD model. The results indicate that the daily rainfall forecasts up to 2-day lead-time improves post-bias correction. This improvement led to the simulation of reliable discharge forecasts at the head of the delta. The inundation extent simulated by the MIKE FLOOD model up to 2-day lead-time was found to match with the observed satellite-based inundation layer with a reasonable accuracy of >31% (fit measure), which is acceptable.