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Investigating the Hydrometeorological Precursors of Floods in the Plains of India

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Abstract: Floods rank among the most devastating natural calamities in the Indian plains, where monsoon regimes and large river systems result in recurrent flooding. Knowing the hydrometeorological precursors of floods is paramount to enhance predictive accuracy and decrease risks. This study investigates the most significant hydrometeorological parameters influencing flood events in the Indian plains and develops predictive models using Machine Learning (Ml) and Deep Learning techniques. This research uses a 60-year historical rainfall record of five cities, Patna, Kanpur, Prayagraj, Haridwar, and Varanasi, collected from the India Meteorological Department (IMD). Robust statistical modelling and feature selection techniques determine the most significant flood predictors. The research adopts some of the machine and deep learning techniques such as Random Forest, Support Vector Machines (SVM), K-Nearest Neighbour (KNN), Long Short-Term Memory (LSTM) networks, Fully Connected Networks (FCN), Deep FCN, Convolutional Neural Networks (CNNs) to evaluate their performance when making flood forecasts. The results show that the intensity of rainfall plays a vital role in determining floods. LSTM networks handle the time sequential data and generate the future rainfall data, providing an FCN-trained model for better prediction accuracy. The proposed Deep Learning - based models demonstrate the effectiveness of early flood warning systems that allow authorities to initiate preventive measures promptly. The results also demonstrate the significance of region-specific flood prevention measures in response to climate variability and land-use changes in the Indian plains. By improving the accuracy of flood forecasts, the study is helpful to disaster management agencies, policymakers, and researchers.

The present research will inspire the integration of onboard data sources from other locations and the model's generalizability to other flood-risk areas. Roll-out of Machine Learning and Deep Learning - driven approaches in flood forecasting will significantly minimize the socio-economic impact of floods, leading to enhanced preparedness and resilience for high-risk communities.

Keywords: *Flood, Rainfall, Rainfall-Threshold, Machine Learning, Deep Learning (LSTM, FCN), Flood Forecasting.*

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I. INTRODUCTION

Floods have always been among the most devastating natural disasters, leading to enormous socio-economic and environmental disruption across the globe. The United Nations Office for Disaster Risk Reduction *(*UN Office, 2015*)* reports that floods account for almost 40% of all natural disasters worldwide. The issue is serious in India and impacts millions of individuals annually because of its distinctive geographical and climatic conditions. The Indo-Gangetic Plains (IGP), covering states such as Uttarakhand, Bihar, Uttar Pradesh (UP), and West Bengal (WB), are characterized by large river systems, monsoon-dominated regimes of precipitation, and hence are highly sensitive to recurrent flooding (Gadgil, 2003).

The Indian summer monsoon (ISM) has always been a blessing to the Indian subcontinent; however, the excess rainfall, whenever it brings, leads to floods on a vast scale and causes damage. The vulnerability to floods in the Indian plains has been additionally aggravated by the increasing volatility and intensity of rainfall events, owing mainly to climate change (IPCC, 2021). Over the last few decades, India has witnessed an increased frequency of cloudbursts, heavy rain events, and altered monsoons (Singh et al., 2018). Such developments have made it imperative for researchers, policymakers, and disaster management authorities to transcend traditional flood management techniques and accept newer prognostic techniques. The key to successful mitigation is understanding the hydrometeorological antecedents i.e., the combination of atmospheric and hydrological factors that provide the setting for flood events

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(Ward et al., 2015). For India, loss of forest cover, monsoon variability, urbanization, and poor drainage facilities also increased flood hazards (Mishra and Singh, 2010*)*. Despite the abundant rainfall and river discharge data accumulated over the decades, flood forecasting in India remains an issue due to the complex meteorological hydrological processes. The current research analyses these cause factors systematically from the vantage point of Artificial Intelligence (Deep Learning). The objective is to develop a strong and efficient flood prediction system using advanced machine learning (ML) and deep learning (DL) algorithms. Flood prediction models based on artificial intelligence (Deep Learning) will benefit the livelihoods, lives, and infrastructure susceptible to India's vulnerable plains.

II. LITERATURE REVIEW

Over the past years, numerous ML and Deep leaning have been explored and applied to enhance the prediction of flood susceptibility, particularly in flood-vulnerable areas such as the IGP of India. Pradhan et al. (2021) employed Random Forest (RF), Support Vector Machines (SVM) and gradient boosting machine (GBM) over the state of Bihar where RF model outperformed others achieving an impressive prediction accuracy of 94.6%. Likewise, Singh and Ramesh (2020) used Long Short-Term Memory (LSTM) models for time serial rainfall and water level data resulting in an accuracy of 92.3%, Another study regarding the Convolutional Neural Networks (CNN) model (Roy and Sharma, 2022), demonstrated its capability in spatial feature extraction for flood prone zone in eastern UP achieving an overall accuracy of 91.8%. The integration of AI techniques has opened new frontiers for reliable prediction, enabling better planning. Further it is noteworthy that several recent global studies offered distinct methodologies but with limitations which our work addresses. For instance, in 2024 (Situ et al., 2024), a deeplabv3+ and LSTM combinations for urban flooding prediction attained high performance metrics NSE: 0.973 but did not incorporate a dedicated rainfall generator like the LSTM. Similarly, a Deep CNN model for fluvial flood inundation prediction trained on hydraulic data in 2020 (Kabir et al., 2020), reporting low error 0–0.5 meters, yet lacked predictive foresight due to absence of rainfall forecasting. Moreover, a global flood risk prediction model using multimodal framework was proposed by Zeng and Bertsimas (2023), where the model attained ROC values of 77%. Interestingly, their model emphasized risk classification rather than spatiotemporal flood forecast. Traditional hybrid models (Mosavi et al., 2018), reported efficiencies around 96%, but these required handcrafted features and lacked scalability in future rainfall synthesis and flood foresights.

This study introduces a novel dual-model framework that integrates LSTM and FCN for future rainfall generation and flood forecasting. Unlike previous flood prediction approaches that either rely solely on historic rainfall data or focus on short term hydrological modelling, our method captures both temporal dynamics and spatial dependencies. The LSTM forecast upcoming rainfall sequence for next 30 years which are then passed into FCN to predict flood occurrences with high spatial resolution. This coupling not only improves lead time but also delivers a flood prediction with 95% accuracy, demonstrating significant advancement over existing models. The two stage pipelines ensure proactive, location-specific and accurate flood forecasts, making it more robust for real world deployment. Our flood forecasting study holds significant real-world implications for disaster risk reduction, urban planning by combining future rainfall generation (using LSTM) with high resolution flood prediction (using FCN). This approach provides advance warning with both temporal foresight and spatial clarity. Such capability is critical in flood vulnerable regions, where early intervention can save lives, reduce economic losses and support emergency logistics. This model can be integrated into a real time flood early warning system used by governments, water resources department, environmental agencies, dam regulating authorities, etc.

III. STUDY AREA

The study has been carried out over the Gangetic Plains of India (GPI) which is considered as one of the most fertile plains across the globe. For the study five major densely populated cities beside the river Ganga have been selected which include Patna in Bihar, Kanpur, Prayagraj, and Varanasi in Uttar Pradesh (UP), and Haridwar in Uttarakhand as shown in Fig.1. The locations (cities) so considered over the GPI, also have a very dense river network, making them highly prone to floods.

IV. DATA AND METHODS

The present work utilizes long-term rainfall data (historical record of 60 years between 1962 to 2022) from the Indian Meteorological Department (IMD) while the data preprocessing and flood forecasting model development has been carried out using Machine learning and Deep Learning. The variable considered includes date, latitude, longitude, and rainfall (in mm). The rainfall values in mm indicate that rainfall is measured in millimetres, representing the water depth that would accumulate on a surface. The extracted rainfall values based on latitude, longitude, and dates are pre-processed using Python. Python is the most widely used programming language in data science due to its powerful libraries such as matplotlib, sklearn, tensorflow, keras, and seaborn. It helps in data collection, preprocessing, and analysis with pandas and numpy (McKinney, 2017). Scikit-learn for Machine Learning (Fabian, 2011) and Deep Learning (Cunha, 2017). We applied a multi-stage procedure for this study. The initial step involved feature engineering and data preprocessing, encompassing dataset cleaning, rain pattern normalization, and selecting the concerned hydrometeorological factors. Then, we trained several machine learning algorithms, such as Random Forest, Support Vector Machines (SVM), and Extreme Gradient Boosting (XGBoost), to identify the non-linear patterns between rainfall attributes and flooding events. To identify spatiotemporal patterns within the data, a Fully Connected Network (FCN) based deep learning model was utilized (Krizhevsky et al., 2012). The model was calibrated to predict the probability of a flood year using trends of monthly and annual rainfall patterns. After validating the model using

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historical records, we continued forecasting flood probabilities for subsequent years (2023–2053) under different rainfall scenarios.

The rainfall observations (1962 to 2022) are firstly computed into monthly and annual rainfall means. The individual rainfall values are grouped monthly and yearly, then each year's total monthly and annual rainfall is calculated and analyzed. We computed the average monthly rainfall values over the years, annual average rainfall, and long-term average rainfall for each location. Further, we assigned standard deviation (σ) to the rainfall value and adjusted it per the location's data. A threshold value is used to find the flood year. Threshold values are calculated as monsoon average rainfall plus 0.x times the standard deviation multiplied by the standard deviation of annual rainfall (threshold = monsoon average rainfall + 0.x * standard deviation of annual rainfall), where any years that touch or crosses the threshold value will be taken flood years as 1 and if not then 0 as non-flood year, and created a preprocessed new dataset for each location. Instead of setting a fixed flood threshold, this method considers how rainfall changed over the years; different regions may have different rainfall variations, so this method ensures a more region-specified flood classification.

We merged all five location datasets into a single dataset to train our machine learning and deep learning model. It increases data size to train on a larger dataset, helps the models learn diverse patterns across different regions and years, and more data reduces overfitting, making predictions more generalized to new data. Rainfall patterns vary across regions; by adding a column 'location' into the dataset, the model can learn location-based trends, helping capture region-specific flood risks and more diverse rainfall patterns, improving feature representation, and learning better correlations between rainfall and floods, improving prediction accuracy.

To train and test the ML model, K-Fold cross-validation (splits=5) was used, a technique which splits data into 5 parts, training on 4 and testing on 1, then repeating the process 5 times. For the deep learning model, data splits into 80 to train and 20 to test. The model is trained for 50 epochs, meaning it sees the entire dataset 50 times to learn better patterns. Here we have used multiple ML and DL models such as Random Forest classifier XGBoost, K-Nearest neighbours (KNN), Logistic regression, Support vector machine, Decision tree, CNN, LSTM, FCN and Deep FCN.

➢ *Fully Connected Network*

FCN is a deep learning model where every neuron in one layer is connected to every neuron in the next layer. The input layer takes raw data features, e.g., rainfall in different months. The hidden layer has multiple layers with neurons which apply the activate functions like ReLU and Sigmoid to learn patterns. The output layer produces final predictions like flood occurrence, yes or no. It models complex non-linear relationships between input features. Each connection in FCN has a weight, and the model learns these weights during training to lower the prediction error. The training utilizes backpropagation, where error is propagated backward to adjust weights using optimization techniques like gradient descent (Heaton, 2017).

Neuron Activation in Hidden Layers

$$\mathbf{z} = W \cdot X + b \qquad \text{(Eq. 1)}$$

Where X is the input feature vector, W is the weight matrix, b is the bias term (learned during training), z is the weighted sum before activation, and ReLU activation is applied: a = max(0, z) Output Layer Calculation

The single neuron applies the Sigmoid function to produce a probability:

$$\hat{y} = \sigma(W * X + b) = \frac{1}{1+e^{-(wx+b}} \qquad \text{(Eq. 2)}$$

Where $\hat{y}$ is the prediction of flood occurrence.

Loss function: Binary cross-entropy $\hat{y}_i$

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}[y_i \, log \, log \, (\hat{y}_i) + (1-y_i)log(1-y_i)] \qquad \text{(Eq. 3)}$$

Where N is the number of samples, y_i is actual flood occurrence, and is predicted probability from the model.

V. RESULTS AND DISCUSSION

➢ *Mean Rainfall Distribution*

Fig.2 shows the monthly rainfall distribution pattern over the considered locations over the GPI as Patna (Fig.2.1), Kanpur (Fig.2.2), Prayagraj (Fig.2.3), Haridwar (Fig.2.4) and Varanasi (Fig.2.5). The x-axis represents the month, and the y-axis represents the rainfall value in mm. Monsoon months, i.e., June (06), July (07), August (08), and September (09), get higher rainfall, which highly influences the chances of flood occurrence. Each box represents the middle 50% of rainfall data (from 25th to 75th percentile), while the horizontal line inside each box denotes the median (50th percentile). The extended lines indicate the minimum and maximum rainfall values, showing high variability in monsoon rainfall, and outliers are the extreme rainfall values for that month.

Annual rainfall trends are shown in the upper rows in Fig.3 (Fig.3.1 to Fig.3.5), representing the trend analysis of rainfall with the line plot. The trend line (blue) shows the general trend over time, with the highest and lowest rainfall values with annotations and a horizontal (dashed) line for average annual rainfall. Deviation from average annual rainfall (Fig.3.1 to Fig.3.5 bottom rows) are shown where it has been calculated from the deviation from mean annual rainfall; grey bars show the normal years, red bars highlight years with above +1 standard deviation (sd) rainfall, and blue bars highlight years with below -1 sd rainfall. It helps to measure rainfall variability; if rainfall exceeds the mean of +1 sd, it indicates an unusually wet year that could be a potential flood risk; if rainfall is below the mean of -1 sd, it indicates an unusually dry year that could mean possible drought.

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Fig.3.1 shows the rainfall distribution for Patna, which has an average annual rainfall of 1105.24 mm, a maximum annual rainfall of 1952 mm in 2022, and a minimum rainfall of 428 mm in 1966. 8 years are found in +1 sd, while 11 years are found in -1 sd from average annual rainfall. Kanpur has an average annual rainfall of 752.88 mm, a maximum annual rainfall of 1660 mm in 1980, and a minimum rainfall of 108 mm in 1998. 9 years are present in +1 sd and 5 years in -1 sd from the average annual rainfall (Fig.3.2). Similarly, Prayagraj has an average annual rainfall of 836 mm, a maximum annual rainfall of 1466 mm in 2003 and a minimum rainfall of 435 mm in 1997 (Fig.3.3). Here, we find 10 years in +1 sd and 8 years in -1 sd from average annual rainfall for the Prayagraj. Fig.3.4 shows the rainfall pattern for Haridwar. It has an average annual rainfall of 568.25 mm, a maximum annual rainfall of 1357 mm in 1988, and a minimum rainfall of 186 mm in 1972. It has 11 years in +1 sd and 8 years in -1 sd from the average annual rainfall. Fig.3.5 depicts the rainfall distribution pattern over Varanasi, which shows an average annual rainfall of 859.28 mm, a maximum annual rainfall of 1760 mm in 1987, and a minimum rainfall of 482 mm in 2009. Here, 8 years are seen in +1 sd and 11 years in -1 sd range from the average annual rainfall.

- *Long-Term Average Rainfall (LPA)*

LPA is the average rainfall recorded over a long period (60-year period for June, July, August, and September (JJAS)). This is used to compare current rainfall patterns with past trends and detect abnormal monsoon variations. The LPA monsoon rainfall is shown in Fig.4. The bar chart shows the average monsoon rainfall for each month, and the error bars show rainfall variability. The more extended error bar shows that rainfall varied extensively over the years, and the less extended bars show more stable rainfall in those years. A dashed red line represents the overall monsoon rainfall average. If rainfall is much below LPA, it may indicate drought, whereas excess rainfall may indicate flood risk. Fig.4.1 shows LPA for Patna. The overall LPA rainfall is 233.52 mm where the month of June receives the least rainfall and varies significantly yearly. July receives the highest rainfall with large variability. August receives moderate rainfall, and September is just below LPA with moderate variability. The LPA for Kanpur (Fig.4.2) shows an overall LPA rainfall of 163.12 mm. Here, June receives the least rainfall with high variability in rainfall each year, July receives the highest with considerable variability, meaning some years have significantly more or less rainfall, August receives moderate rainfall, and September is slightly above LPA with considerable variability (Fig.4.2). Fig.4.3 shows LPA for Prayagraj. The overall LPA rainfall is 185.73 mm, June receives the least rainfall with high variability in rainfall each year, July receives the highest rainfall, August receives above LPA rainfall with very high variability, and September is slightly below LPA with considerable variability. Fig.4.4 shows LPA for Haridwar. The overall LPA rainfall is 185.73 mm, June receives the least rainfall with high variability in rainfall each year, July receives the highest rainfall with high variability, August receives above LPA rainfall with very high variability, and September receives below LPA with large variability. The LPA for Varanasi is shown in Fig.4.5. The overall LPA rainfall is 193.12 mm, June receives the low rainfall, July receives the highest with considerable variability, meaning some years have significantly more or less rainfall, August receives above LPA rainfall with high variability in rainfall each year and September is slightly below with very large variability.

- *Daily Rainfall with Flood Risk*

Rainfall exceeding 100 mm rainfall in a day causes urban and river flooding (Dhar and Nandragi, 2000). Across different parts of the world, 100–150 mm of rain in a single day leads to severe river flooding, while rainfall more than 200 mm in a day often results in flash floods (Ashley and Ashley, 2008). Fig.5 shows the dates where rainfall occurred, 80 mm or more. With the values assigned as rainfall of 100 mm caused flood, 150 mm caused widespread flood, and 200 mm caused flash in the presented region (Dhar and Nandragi, 2000; Ashley and Ashley 2008). Fig.5.1 shows Patna's extreme rainfall dates (> 100 mm) from 1962 to 2022. Subsequent figures (Fig.5.2, Fig.5.3, Fig.5.4, Fig.5.5) show the dates exceeding rainfall of 100 mm in a day for cities Kanpur, Prayagraj, Haridwar, and Varanasi, respectively.

- *Flood Risk Based on Rainfall Threshold*

Fig.6 shows the flood years over the cities with the assigned threshold value according to their region-specified thresholds. The years in those regions that crossed the threshold rainfall value were set to flood year as 1 in the dataset, and those that did not were set as 0.

In Fig.6.1, flood risk for Patna has been computed with flood years based on rainfall threshold value with $\sigma = 0.75$, red bars represent the flood year with rainfall values in mm from 1962 to 2022. The years that had floods included 1975, 2003, 2019, and 2021, matching with flood records (British Pathé, 1975; Hindustan Hindi News, 2019; FMISC, 2021). Similarly, for Kanpur, flood years are based on rainfall threshold values with $\sigma = 0.4$ are computed and shown in Fig.6.2. The red bars represent the flood year with rainfall values in mm, from 1962 to 2022. Fig.6.3 shows Prayagraj flood years based on rainfall threshold value with $\sigma = 0.5$ with flood years, including 1978, 2013, and 2020, matching with flood records (TOI, 2020). Fig.6.4 and Fig.6.5 show the cities, Haridwar and Varanasi, respectively with flood years based on rainfall threshold value with $\sigma = 0.5$ and $\sigma = 0.6$. Haridwar had floods in 2010, and 2021, matching with flood records (Central Water Commission, 2011; DDMA, 2022). The city of Varanasi showed floods in 1978 matching with flood records (Mishra, 2022).

- *Forecasting the Flood Years with FCN*

Multiple ML and DL models were used for training and testing, which included RF, XGBoost, KNN, Logistic regression, SVM, Decision tree, CNN, LSTM, FCN, and Deep FCN. Fig.7 shows the results for these training and testing and accuracy comparison (Fig.7.1) of different ML and DL models. The FCN has the highest accuracy, i.e., 95%, which caused this model to be chosen for forecasting the flood.

We have performed rainfall prediction for the next 30 years (2023 to 2053) and subsequent flood forecasting using

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LSTM and FCN model. The LSTM is designed to predict and process sequential data, such as time serial data. It has a memory shell that helps them remember important information over long sequences (Hochreiter and Schmidhuber, 1997). Here, LSTM generates annual rainfall for the next 30 years based on historical rainfall data. Then after, this information is sent to the FCN model to predict the probability of floods by loading a pre-trained FCN model, where the model takes multiple rainfall-related features and gives the probability of flood. The results are visualized into a plot showing flood prediction. This combined LSTM-FCN approach helps in long-term flood forecasting by predicting future rainfall first and then assigning flood risks based on the data later.

Fig.8.1 shows 2030, 2032, and 2044 with an extremely high chance of facing a flood in Patna. Similarly, Fig.8.2. shows high flood risk years as 2039, 2043, and 2045 for Kanpur. Fig.8.3 shows years 2032, 2039, 2043, and 2047 as extreme flood risk years predicted for Prayagraj. The city of Haridwar (Fig.8.4) shows 2032, 2037, 2039, 2043, and 2044 as high flood-risk years. Fig.8.5 shows 2032, 2043, and 2049 with an extremely high chance of facing a flood in Varanasi.

VI. CONCLUSIONS

Floods pose a significant threat to life, infrastructure and agriculture, especially in the flood prone regions of India. The present research develops a reliable flood forecasting system using ML and Deep learning techniques by analysing long term rainfall trends. We investigated the potential flood years in the upcoming future with high accuracy. The use of advance models such as RF, SVM, LSTM CNN, FNN enable us to capture both spatial and temporal pattern in the data, these models, trained and validated on historical data from 1962 to 2022, demonstrated promising accuracy level in flood forecasting, with FCN model achieving 95% predictive performance. Moreover, the merging of multiple datasets while maintaining location specific attributes allowed for a more generalized and robust model training process. This approach can be extended to other flood prone regions for regional analysis.

Future work may include integrating real-time weather data, river discharge levels, satellite imagery to enhance the prediction capabilities further. Thus, this research contributes toward building a data-driven, proactive approach for assessing flood risks and protecting vulnerable communities.

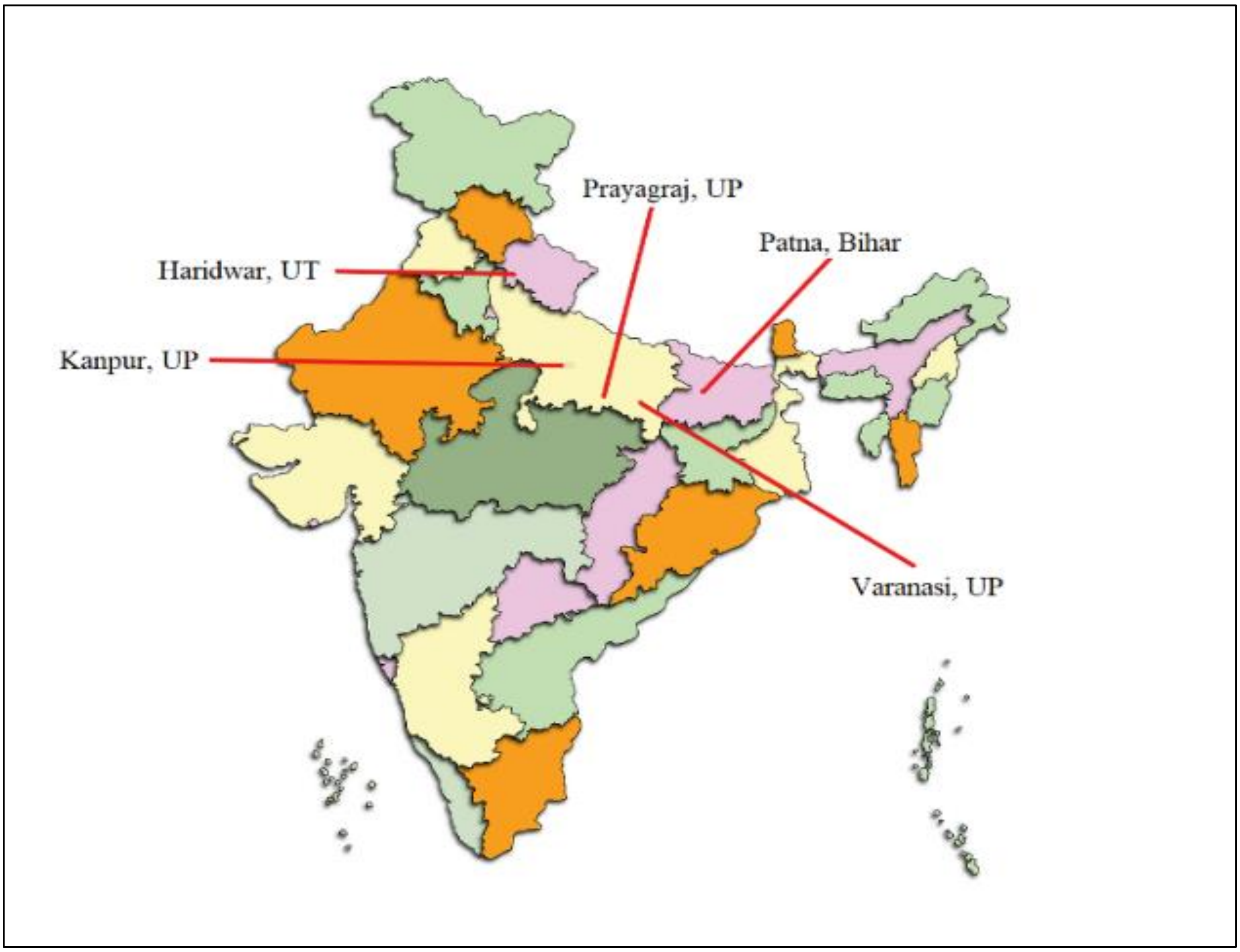

Fig 1 Map of the Study Area with the Five Cities Considered

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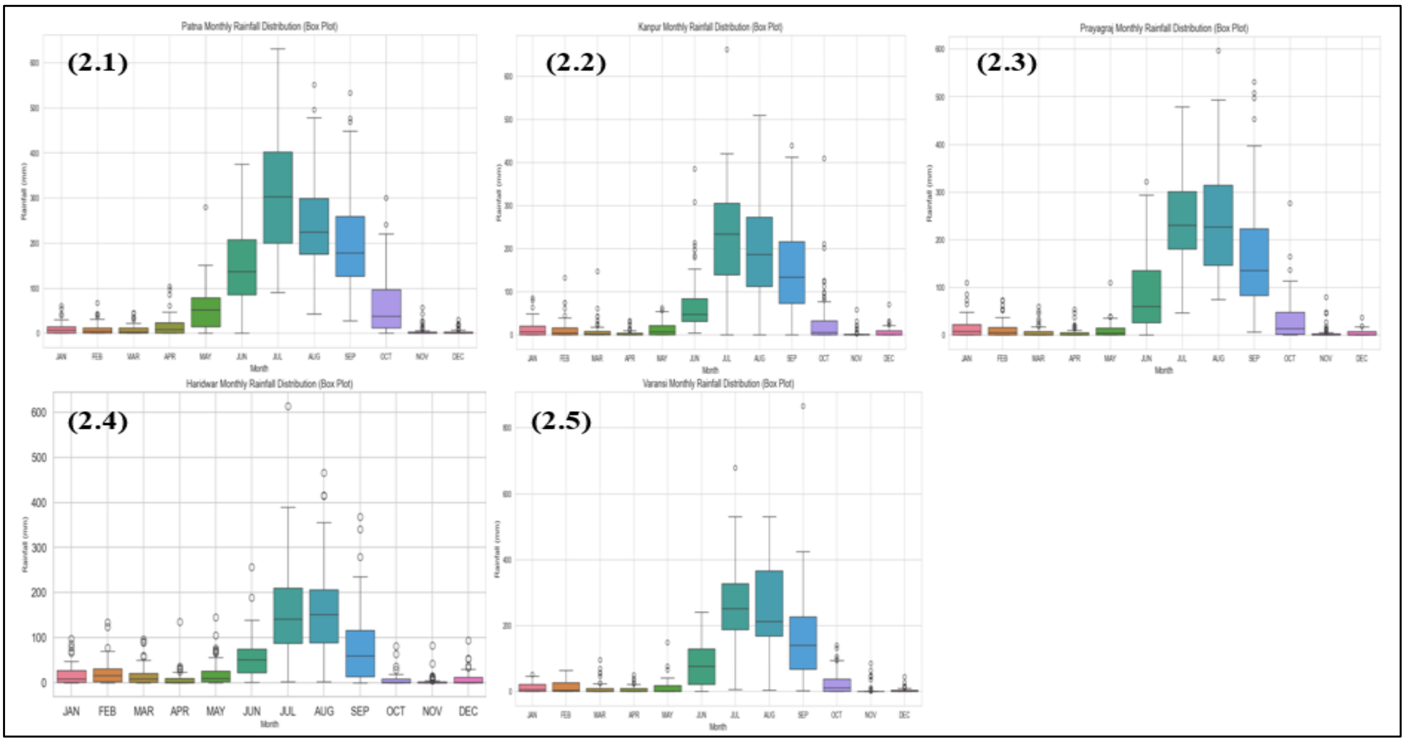

Fig 2 Monthly Rainfall Distribution over the Districts of (2.1) Patna; (2.2) Kanpur; (2.3) Prayagraj; (2.4) Haridwar; and (2.5) Varanasi during 1962-2022

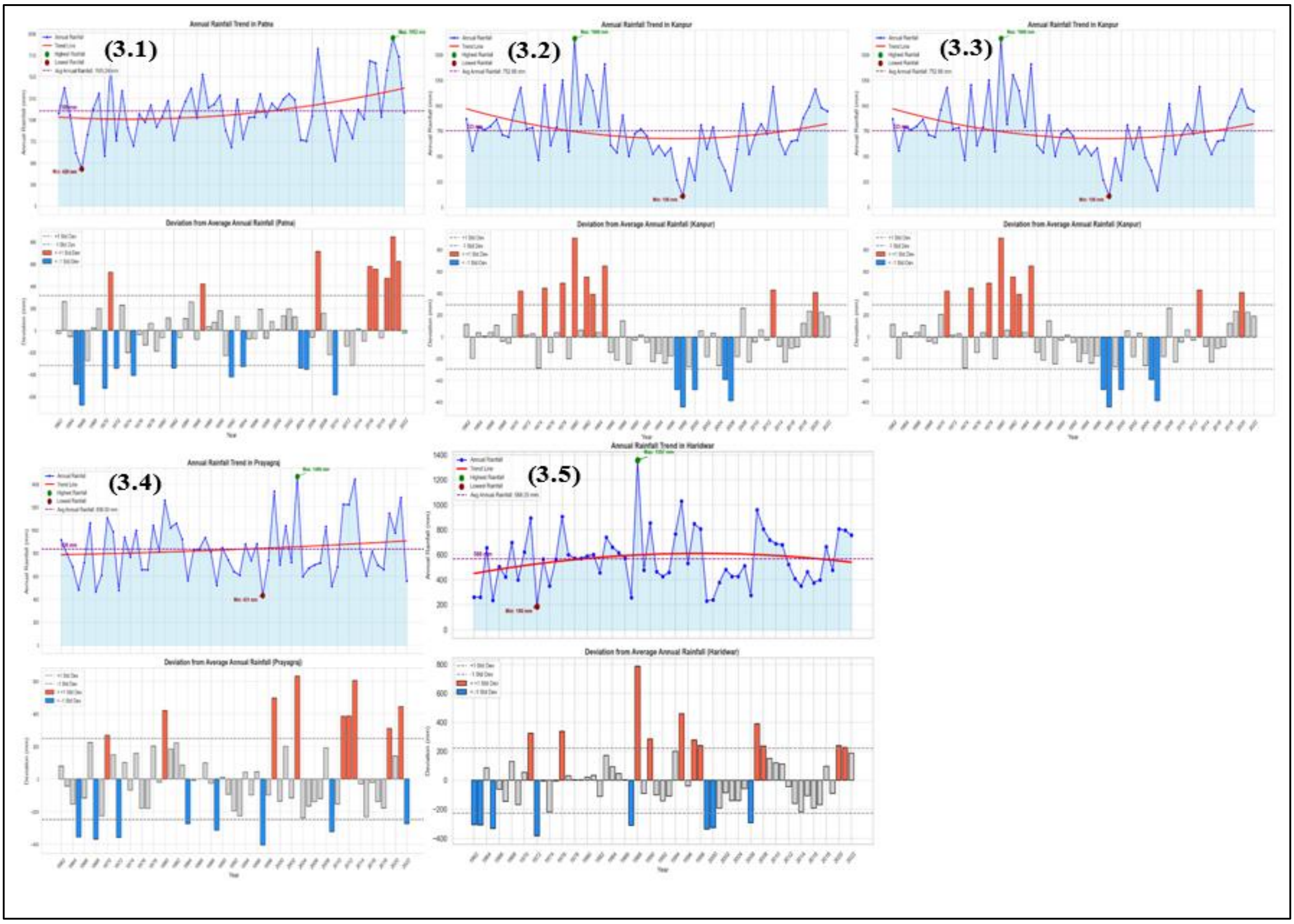

Fig 3 Annual Rainfall Trend over the Districts of (3.1) Patna; (3.2) Kanpur; 32.3) Prayagraj; (3.4) Haridwar; and (3.5) Varanasi during 1962-2022

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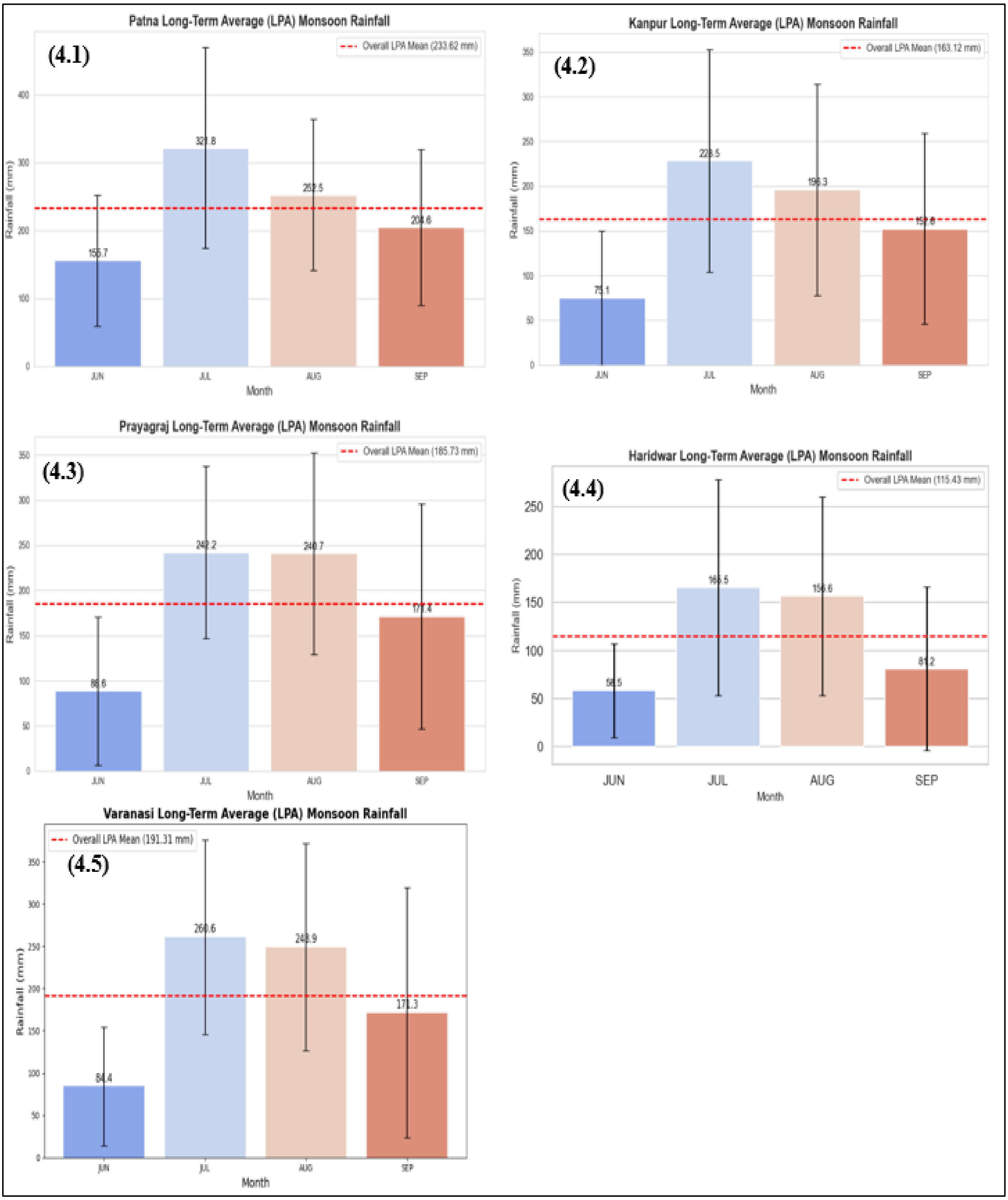

Fig 4 Long-term Average Rainfall (LPA) over the Districts of (4.1) Patna; (4.2) Kanpur; (4.3) Prayagraj; (4.4) Haridwar; and (4.5) Varanasi during 1962-2022

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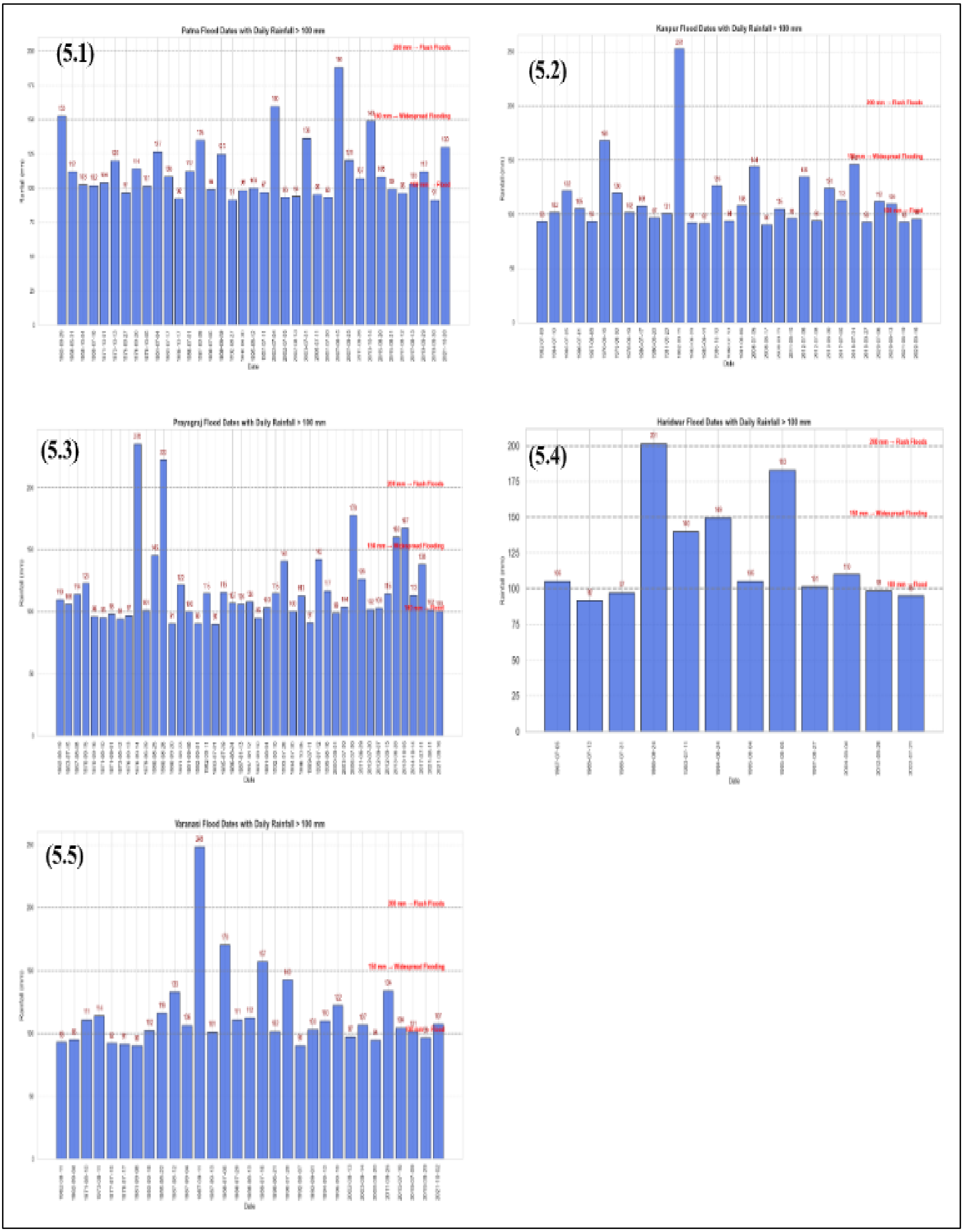

Fig 5 Dates of Flood Happened by Rainfall >100 mm over the districts of (5.1) Patna; (5.2) Kanpur; (5.3) Prayagraj; (5.4) Haridwar; and (5.5) Varanasi during 1962-2022

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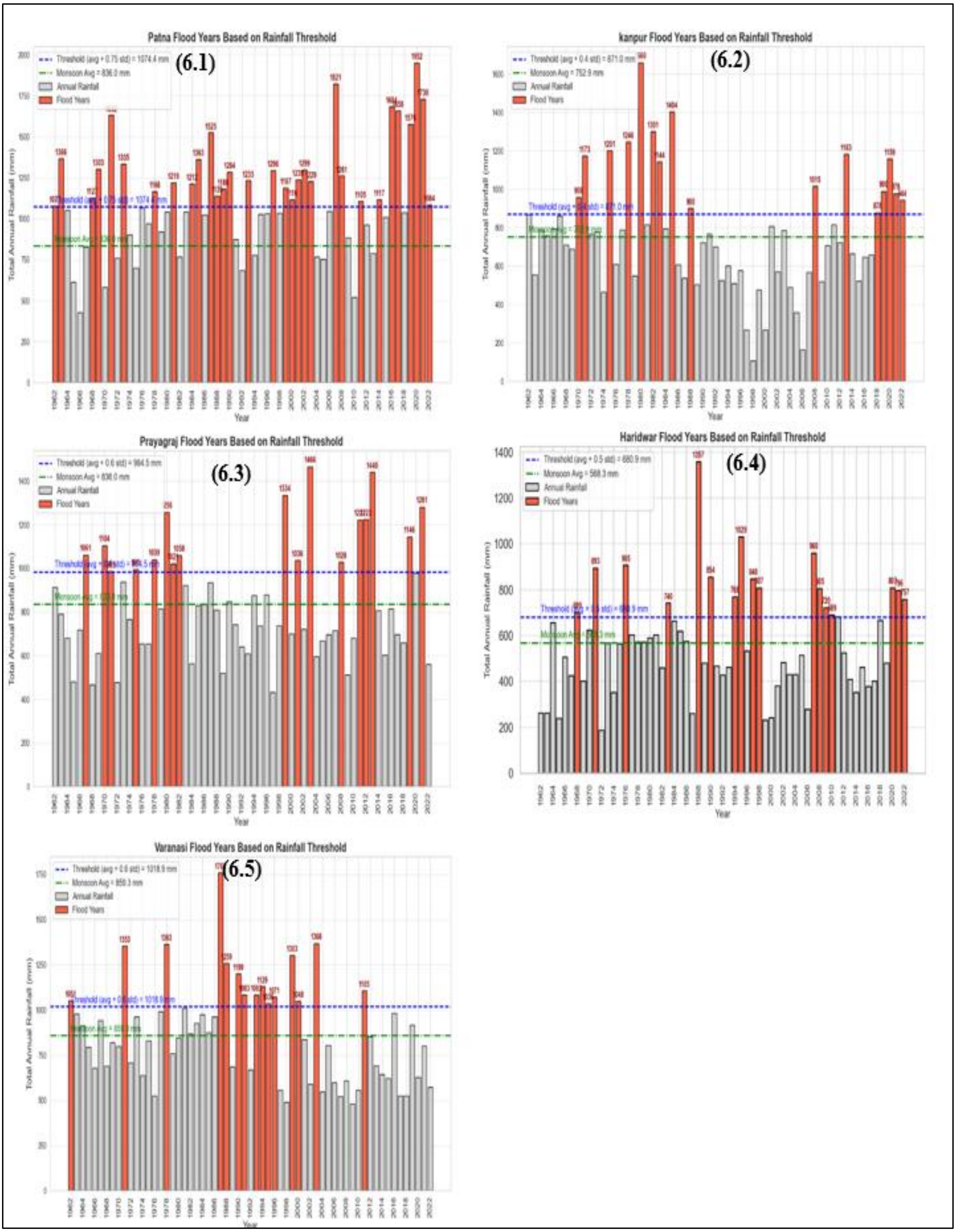

Fig 6 Flood Years over the Districts of (6.1) Patna; (6.2) Kanpur; (6.3) Prayagraj; (6.4) Haridwar; and (6.5) Varanasi during 1962-2022

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(7)

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                Name     Score
2  LogisticRegression  0.934426
4        DecisionTree  0.934426
3                 SVM  0.934426
0        RandomForest  0.868852
1                 KNN  0.836066
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.9464 - loss: 0.1109
FCN - Test Accuracy: 0.9508
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.9146 - loss: 0.2585
CNN - Test Accuracy: 0.9344
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 17ms/step - accuracy: 0.8397 - loss: 0.3177
LSTM - Test Accuracy: 0.8689
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 16ms/step - accuracy: 0.9250 - loss: 0.2264
Deep FCN - Test Accuracy: 0.9344
       Name     Score
0       FCN  0.950820
1       CNN  0.934426
3  Deep FCN  0.934426
2      LSTM  0.868852
```

(7.1)

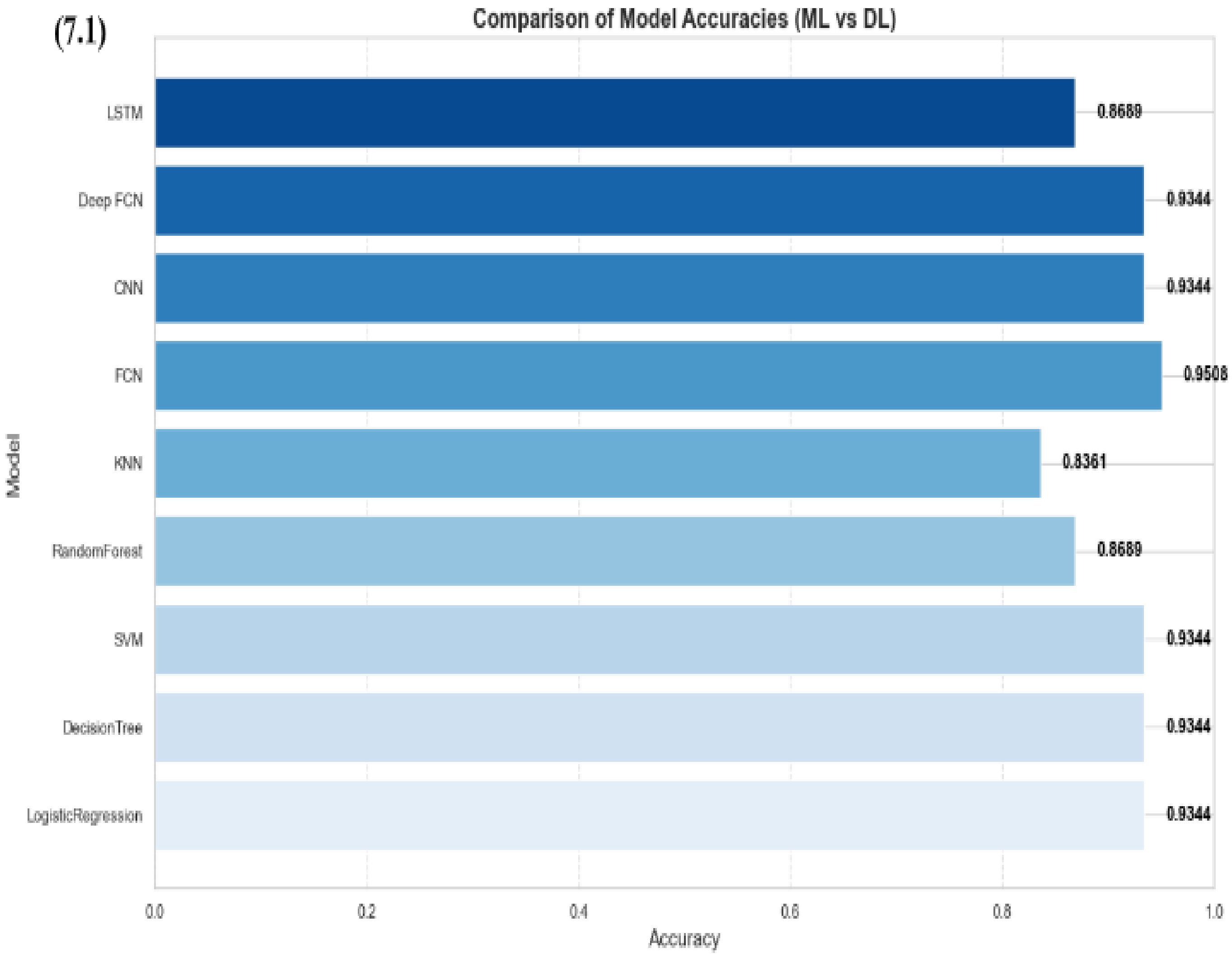

Fig 7 Chart of Machine and Deep Learning Model Accuracy and Fig.7.1: Deep Learning And Machine Learning Models' Accuracy Comparison

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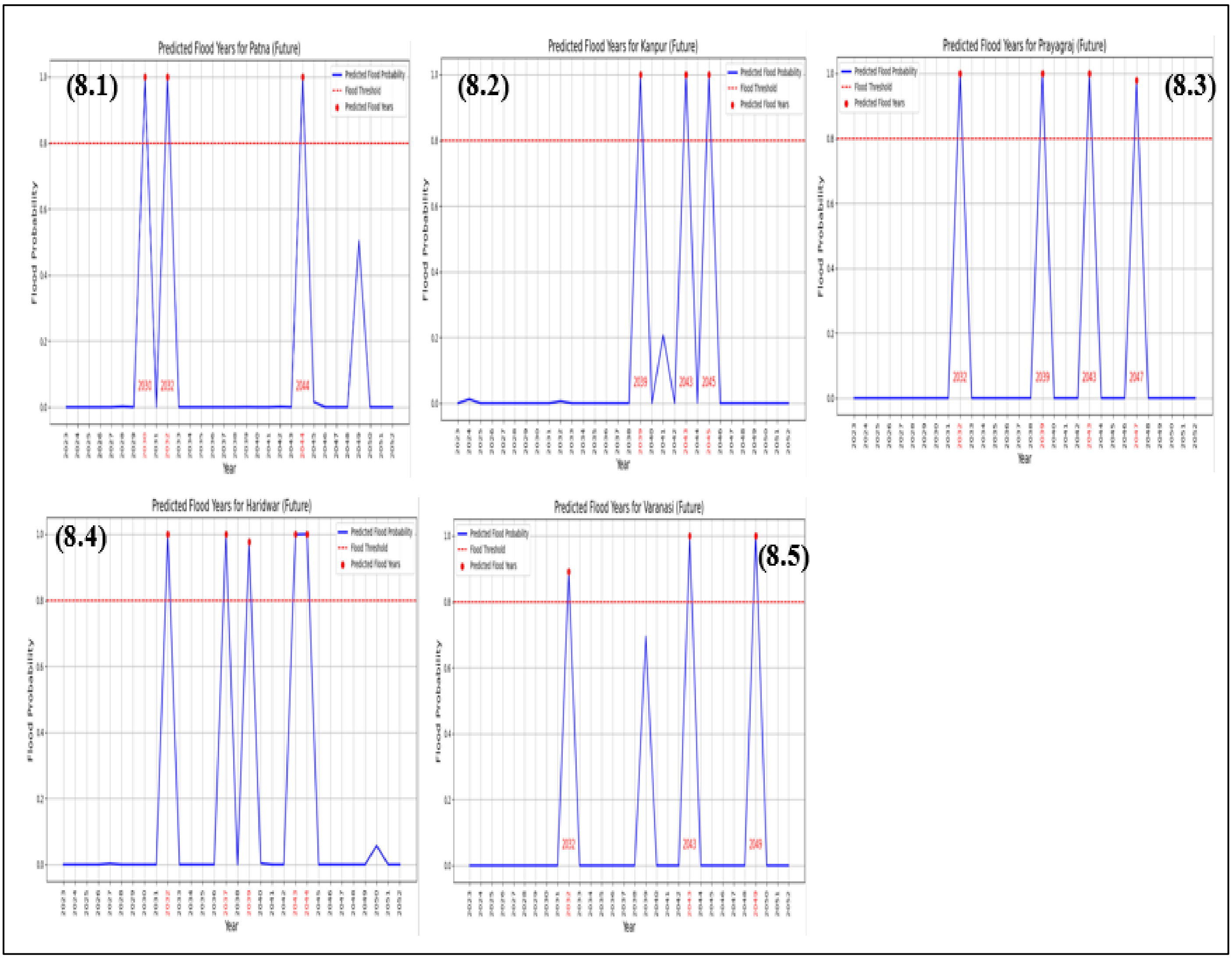

Fig 8 FCN Predicted Flood Year over the Districts of (8.1) Patna; (8.2) Kanpur; (8.3) Prayagraj; (8.4) Haridwar; and (8.5) Varanasi for 2022-2052

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