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Evaluating the Performance of CHIRPS Satellite Rainfall Data for Streamflow Forecasting

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Abstract
Streamflow forecasting can offer valuable information for optimal management of water resources, flood mitigation, and drought warning. This research aims in evaluating the effectiveness of CHIRPS satellite rainfall data in comparison with IMD gridded Rainfall Data and development of various flow forecasting models. Daily rainfall data for three decades (1983–2012) over the Nethravathi Basin, Karnataka, India is used for analysis. The analysis is carried out for the monsoon season (June–September), out of which 70% data considered for training the model and remaining for testing. Different input combinations are developed, and soft-computing methods like ANFIS, GRNN, PSO-ANN, and ELM are applied for flow forecasting on a temporal scale. The model performance is evaluated using various statistical indices like NNSE, RRMSE, and MAE. The results indicate that CHIRPS rainfall showed better performance in comparison with IMD data. ELM expressed an enhanced effect when compared to all other methods. The usefulness and effectiveness of CHIRPS data compared to IMD data has been explored.

Keywords CHIRPS · ELM · Forecasting · Satellite rainfall · Streamflow · Nethravathi River

1 Introduction

Streamflow forecasting plays a primary role in planning of water management for agriculture, hydropower generation, industry, and environmental water. Identification of suitable model for predicting streamflow is essential for effective utilisation of water. The model which simulates the river flow based on previously recorded flow amount will be economically preferable for research as well as practical purposes. Although the precipitation data are available in a different format, majority of researchers are attracted towards ground-based or station based data. Recently, very few researchers started exploring the usefulness and effectiveness of

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satellite-based rainfall data. The streamflow prediction models can be classified into two broad categories, linear models and non-linear models. Linear models include Auto-Regressive (AR), Moving Average (MA), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), Auto-Regressive Integrated Moving Average with exogenous output (ARIMAX), Linear Regression (LR) and Multiple Linear Regression (MLR) which are linear (Abrahart and See 2000; Maier and Dandy 2000; Wu et al. 2009; Valipour 2015). The streamflow forecasting depends upon factors like precipitation, evapotranspiration, temperature, snowpack etc. These variables make streamflow process non-linear. Linear models perform better when the data rely upon past observations, however, they execute ineffectively when the data also depends upon other exogenous factors. The limitations of linear models motivate the researchers to further develop efficient models.

The computer era motivated many hydrologists to use the Artificial Intelligence (AI) based models for time series forecasting. AI has the inherent ability to capture and reproduce both non-linear components and non-stationary trends of the hydrological time series with increasing degree of sophistication and statistical precision. AI has established its unique signature in the field of forecasting or prediction of various hydrological phenomena (Yaseen et al. 2015). Among the AI models, Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Generalised Regression Neural Network (GRNN), Particle Swarm Optimization – ANN (PSO-ANN) and Extreme Learning Machine (ELM) models have an important place in modelling of streamflow data. Many researchers have investigated the potential of AI techniques in modelling watershed runoff based on rainfall inputs.

The aim of building a model is to maximize its usefulness. Complexity, reliability, and ambiguity, must be considered for developing the model. ANFIS in modelling may include all reasons which are discarded in flawless models while it may ignore some reasons which are considered in physically-based models (Hundecha and Bardossy 2001). Kisi (2005) employed neural network and neuro-fuzzy approach for estimating suspended sediment concentration. Cobaner (2011) used ANFIS - Sub Clustering (ANFIS-SC) and ANFIS - Grid Partition (ANFIS-GP) model for evapotranspiration estimation and found ANFIS-SC model yields sensible accuracy with less calculations, contrasted with the ANFIS-GP and neural network models. Sanikhani and Kisi (2012) developed ANFIS-SC and ANFIS-GP for monthly stream-flow forecasting. Hadi and Tombul (2018) used wavelet transformation as a pre-processing tool in data-driven models to forecast week-ahead streamflow. Specht (1991) proposed the concept of GRNN. GRNN approximates the input and output vectors between any arbitrary function, and directly draw the function estimate from training data (Cigizoglu 2005). Kisi (2008) compared three different ANN techniques viz. Feed Forward Neural Network (FFNN), GRNN and Radial basis ANN (RBF) for forecasting one month-ahead streamflow. GRNN showed better performance in comparison with other ANN techniques. Diop et al. (2018) used Support Vector Regression (SVR) and GRNN to predict one day ahead daily river flow at Upper Senegal River basin, West Africa. The result shows that SVR displays a superior performance to GRNN.

The advent of evolutionary computation techniques like Particle Swarm Optimization (an algorithm based on social psychology) motivated researchers to hybridize with AI techniques. Salerno (1997) proposed the concept of PSO-ANN. Nasimi et al. (2011) used PSO-Back Propagation algorithm to estimate the Permeability of Mansuri Bangestan reservoir, Iraq. Sudheer et al. (2014) hybridised PSO algorithm with Support Vector Machine for forecasting long-term streamflow over Swan River and St. Regis River, United States. The study suggests that SVM could be a better alternative for predicting monthly streamflow as it provides a high degree of accuracy and reliability.

Huang et al. (2006) proposed ELM, a new data-driven algorithm for single hidden layer feed-forward networks to overcome the limitations of FFBP-ANN. The practice of ELM in several research areas like land displacement prediction (Lian et al. 2012), hydrological flow series prediction (Atiquzzaman and Kandasamy 2016) and dew point estimation (Deka et al. 2018). Yaseen et al. (2018) studied the reliability and effectiveness of ELM in forecasting one-step-ahead stream-flow for three temporal pattern (daily, mean weekly and mean monthly) over Johor River, Malaysia. The results of the ELM approach showed dominance and precise forecasting over ANN models.

Over recent decades, many gridded precipitation datasets are available for suitable large-scale hydrological applications. The datasets differ in terms of source (gauge, radar, satellite, analysis, or reanalysis, or combinations of sources), design objective (temporal homogeneity, instantaneous accuracy or both), spatial resolution (from 0.05° to 2.5°), spatial coverage (from continental to global), temporal resolution (from 0.5 h to monthly), temporal span (from ~1 to 115 years), and latency (from ~3 h to several years) (Beck et al. 2017). Casse et al. (2015) evaluated the strengths of various precipitation products to predict the flood events of Niger River in Niamey. Liu et al. (2017) found that PERSIANN-CDR satellite rainfall data can simulate the streamflow over the upper Yellow and Yangtze River basins on the Tibetan Plateau. Recently, Maggioni and Massari (2018) gave a review on most prevalent satellite precipitation products and their errors and uncertainties, that could play a significant role in hydrological modeling. Climate Hazards InfraRed Precipitation with Stations (CHIRPS) satellite rainfall (Funk et al. 2015) is a recent product, whose potential is yet to evaluate in the quasi-global scale (Beck et al. 2017). Evaluation of CHIRPS satellite rainfall for drought monitoring studies was conducted by Shrestha et al. (2017); Gao et al. (2018). Few researchers used the Soil Water Assessment Tool (SWAT) and CHIRPS rainfall to forecast streamflow (Tuo et al. 2016; Le and Pricope 2017).

Many researchers often use ground-based or station based rainfall data for flow forecasting. Recently, few researchers are motivated to explore the potential of satellite based rainfall products and their influence on river flow forecasting. From the literature survey, it was observed that only a limited number of studies conducted in assessing the potential of CHIRPS rainfall data in streamflow forecasting. Till date, no studies are carried out with the application of Artificial Intelligence (AI) techniques to forecast streamflow using CHIRPS rainfall data as inputs. This research tries to explore the potential or applicability of CHIRPS rainfall data for flow forecasting gauged at Bantwal station of the Nethravathi basin, Karnataka, India using soft-computing techniques like ANFIS, GRNN, PSO-ANN, and ELM. The performance of these models is measured using various statistical indices. The gridded rainfall data of Indian Meteorological Department (IMD) (Pai et al. 2014) is served as inputs and streamflow forecasting carried out for the former models using ANFIS, GRNN, PSO-ANN and ELM for comparative performance evaluation. The article is structured as follows: Section 2 provides information on the Study Area. Section 3 discusses the methodology followed up in the study. The model results are portrayed in Section 4, and a comparison between IMD rainfall and CHIRPS rainfall is discussed in Section 4.3.

2 Description of Study Area and Data

2.1 Study Area

Nethravathi Basin (shown in Fig. 1) is located in the Western Ghats of Karnataka and drains an area around 4300km^2. The west-flowing River Nethravathi originates at Gangamoola and

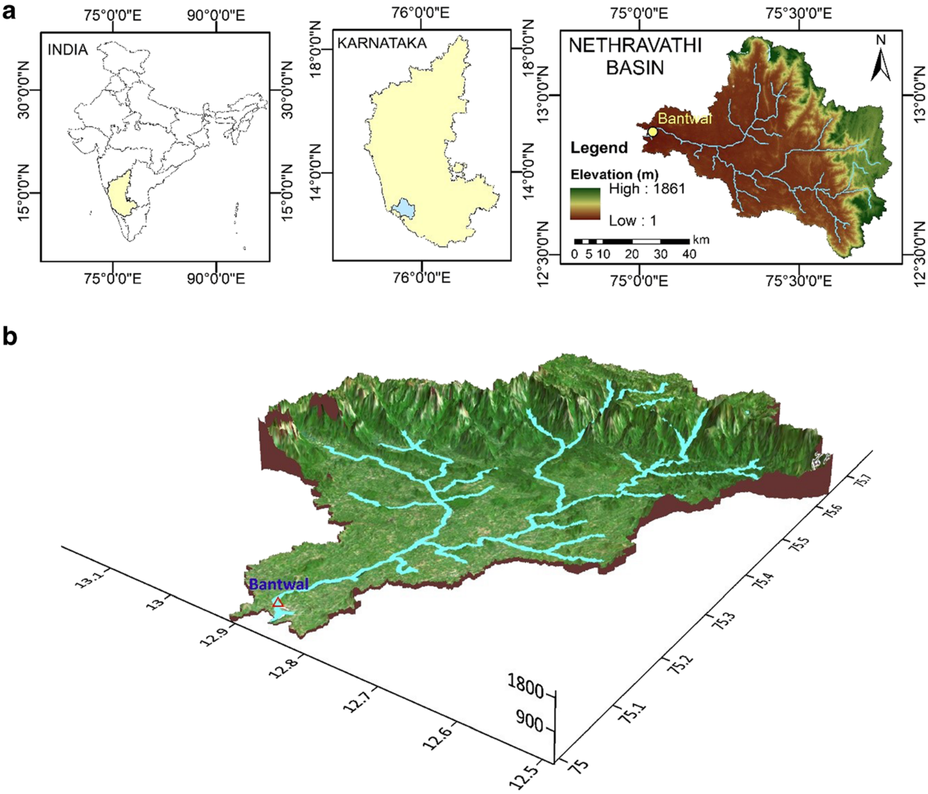

Fig. 1 Study Area - (a) The Nethravathi Basin (b) A three-dimensional representation DEM of the river basin with stream network and Bantwal discharge gauging station

reaches the Arabian Sea in Mangaluru. River Kumaradhara, a major tributary confluences with River Nethravathi at Uppinangady. The extents of the basin are 12°29′21.17″ to 13°11′9.05″ north latitudes and 74°59′23.95″ to 75°47′27.06″ east longitudes. The Central Water Commission (CWC) has set up a stream gauge station at Bantwal to record discharge in the river, around 20 km upstream from the river mouth. South West monsoon (June–September) is predominant than post-monsoon (October – May) in the study area. The watershed receives an annual rainfall around 3600 mm. Due to laterite soil and heavy rainfall over the region support luxurious growth of vegetation. The Western Ghats are mountainous region with thick forest, which are located in the upper part of the basin. The basin has different types of forest varying stages from evergreen scrub, to fully grown forest (Ganasri and Ramesh 2016). The coolest part of the year is during June to September (Southwest Monsoon) with the average daily temperature below 25 °C. Between March to May the mean daily temperature is about 35 °C, the weather is highly humid throughout the year.

2.2 Data Collection

The rainfall data of 13 grid points within the Nethravathi basin provided by the India Meteorological Department (IMD), Pune was used in the study. The IMD gridded rainfall product of spatial resolution of 0.25° × 0.25° was extracted for the years 1983 to 2012 to compute the areal average precipitation over the basin using the Thiessen Polygon method. Under GIS analysis, the grid points of IMD Rainfall data were overlaid on the basin, and the daily rainfall data of around 13 grid points falling within the basin were extracted using the grid extraction tool as text files for the years 1983–2012. The Thiessen Polygons were created for all the grid points to demarcate the influence area of each grid and the areal average rainfall over the Nethravathi Basin was computed. The monsoon season over the region starts from June and ends by September. Only the monsoon season data was sorted for present analysis.

CHIRPS is a satellite based precipitation product which has provides about three decades of quasi-global rainfall dataset. This gridded rainfall time series data is available from the year 1981 to near-present at a spatial resolution of 0.05° with integrated station data. The average rainfall data over the basin was extracted using Google Earth Engine tool and sorted for monsoon season.

The streamflow data of Nethravathi basin gauged at Bantwal hydrological observation station (located at 12° 52′ 51″ N Latitude and 75° 02′ 27″ E Longitude) was used in the present research. The streamflow data of the years 1983 to 2012 was considered for modelling. The analysis was carried out only for the monsoon season streamflow records.

The data analysis includes, the maximum, minimum, mean, standard deviation, coefficient of variance and Skewness of all variables influencing streamflow are tabulated in Table 1. IMD daily rainfall maximum is found almost half of CHIRPS rainfall in training data. Similar behaviour is also seen in testing data. Also, the average IMD rainfall value is slightly less than CHIRPS rainfall value in both scenarios of training and testing. Very high variability is seen in CHIRPS data in both training and testing compared to IMD data. The high skewness represents the majority of data concentration in the CHIRPS rainfall towards the tail part compared to IMD data during training. However, in the testing dataset skewness is almost similar in both the rainfall product. In the case of streamflow, the maximum discharge is seen in testing data and slightly less in training data. The average streamflow in training data is less when compared with testing data. The standard deviation of discharge data is nearly the same in both training and testing. The variance is high in training streamflow data and slightly less in testing data. High skewness represents that majority of data concentration in streamflow data towards the tail part, and it is seen in both training and testing dataset.

Table 1 Data Statistics of Input Parameters

Statistics	Training Data			Testing Data		
	IMD Rainfall (mm)	CHIRPS Rainfall (mm)	Streamflow (m^3/s)	IMD Rainfall (mm)	CHIRPS Rainfall (mm)	Streamflow (m^3/s)
Minimum	0	0	0.264	0	0	0.000
Maximum	160.729	337.236	5506.200	137.718	279.192	5610.000
Mean	19.729	22.185	838.926	16.891	24.020	922.007
Standard Deviation	21.147	41.571	734.739	19.829	32.670	733.970
Coefficient of Variance	1.072	1.874	0.876	1.174	1.360	0.796
Skewness	1.995	3.032	1.670	2.267	2.232	1.543

3 Methodology

The selection of input variables was carried out based on Autocorrelation function (ACF) and Partial autocorrelation function (PACF) of rainfall and streamflow data. The ACF and PACF indicated that, the streamflow values were autoregressive and having decent autocorrelation up to four lags. Likewise, the ACF and PACF of rainfall data were also autoregressive and the rainfall up to one lag held very good autocorrelation.

Following are the model combinations considered in this study:

Model 1–$R_t + S_t \rightarrow S_{t+1}$

Model 2–$R_{t-1} + R_t + S_{t-1} + S_t \rightarrow S_{t+1}$

Where R_{t-1} and R_t are input Rainfall values with a lag of one day and present day rainfall respectively. S_{t-1} and S_t are input Streamflow values with a lag of one day and present day streamflow. S_{t+1} is one day ahead forecasted streamflow. Figure 2 provides a schematic representation of the methodology adopted in this study. The soft-computing methods like ANFIS, GRNN, PSO-ANN, and ELM were developed and implemented using MATLAB program codes.

3.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a blend of Fuzzy Inference System and Neural Network algorithm. The Neural Network algorithm is used to tune the parameters of membership function, which has a better fitting to the training data. Based on “if-then rule” in the inference operation ANFIS is classified into three classes namely, Mamdani (Mamdani and Assilian 1975), Tsukamoto and Sugeno

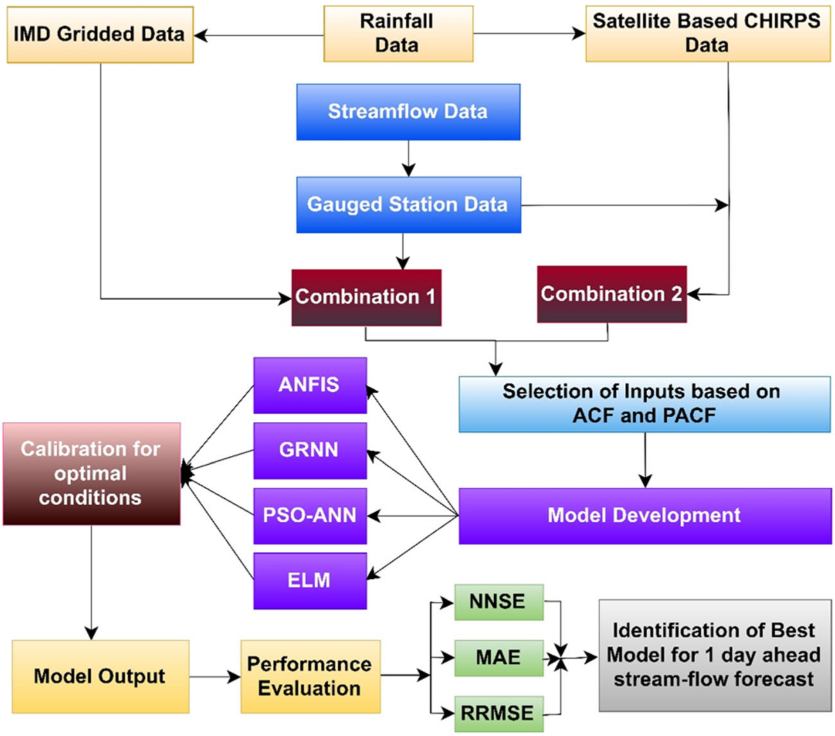

Fig. 2 Methodology adopted

(Takagi and Sugeno 1985). Among these three, Mamdani is the most used Fuzzy Inference System. However, the Sugeno FIS is more effective, robust and computationally intractable in the defuzzification process. The concise output of Sugeno, make the ANFIS model more appropriate for adaptive techniques (Sanikhani and Kisi 2012).

ANFIS has two models namely, ANFIS Grid Partitioning (ANFIS-GP) and ANFIS Sub Clustering (ANFIS-SC). Out of these two, ANFIS-GP is most commonly used model. The each input variable in ANFIS-GP model is divided into several membership functions (MF), and rules are created with each MF with all other MF of same and other variables. Based on number of variables, the number of rules increase exponentially. The number of rules is equal to p^q, where p and q are number of membership function and number of variables respectively.

3.2 Particle Swarm Optimization-ANN (PSO-ANN)

The supportive and social performance shown by several species to fill their requirements in the multidimensional search space, inspired the researchers to develop PSO. The model process starts with the initialization of random particle collection. The position of particles represent the biases and weights of ANN. The selection of particles is purely random. In the next stage, the hybrid PSO model is trained with initial biases and weight factors.

Later, the convergence of the trained network is checked, by computing the error between predicted and actual values. At each iteration, the error is reduced by altering the position of particle. The fresh error, which is supposed to be smaller than the past step is calculated for each step. This method continues until one of the stop criteria is fulfilled. More detailed information about the PSO-ANN algorithm can be seen in (Armaghani et al. 2014; Rukhaiyar et al. 2018)

3.3 Generalised Regression Neural Network (GRNN)

Specht (1991) proposed probabilistic neural network (PNN), it applies to classification problem only, but cannot solve the continuous data problem. The need for a learning algorithm which has the ability to learn dynamic patterns, predict, and to deal with regression problems was proposed by Specht in 1991 called GRNN. The GRNN architecture has a total of four layers namely, Input layer, Sample layer, summary layer and linear layer. More information about the mechanism of GRNN algorithm can be seen in (Kisi 2008).

3.4 Extreme Learning Machine (ELM)

The iterative alteration of network parameters led to low learning rate and low training speed of gradient-based algorithms. ELM, an innovative training algorithm was presented by Huang et al. (2004). The hidden nodes are selected randomly and using the Moore Penrose generalized inverse the output weights of single-layer feed forward neural networks are determined analytically. Using N arbitrary samples and L hidden nodes, $(a_i, b_i) \in R^n \times R^m$ ($i = 1, 2, \ldots, n$) and activation function $g(x)$ the SLFNN models are presented as:

$$\sum_{i=1}^{L} \gamma_i g_i\left(a_j\right) = \sum_{i=1}^{L} \gamma_i g_i(p_i \cdot q_i \cdot a) \tag{1}$$

where $j = 1, 2, \ldots, N$.

Where $p_i = [p_{i1}, p_{i2}, \ldots p_{in}]^T$ is input weight matrix which is associated with hidden layer nodes, q_i is the hidden layer node bias, $\gamma_i = [\gamma_{i1}, \gamma_{i2}, \ldots \gamma_{im}]^T$is output weight matrix which is linked to the hidden layer as nodes.

3.5 Performance Evaluation

The evaluation metrics gauge the model performance and assess the degree of confidence one can have on model predictions. The following are the statistical indices adopted:

1. Normalized Nash-Sutcliffe Efficiency (NNSE)

$$NNSE = \frac{1}{2 - NSE} \tag{2}$$

Where

$$NSE = 1 - \frac{\sum_{x=1}^{N} (O_x - P_x)^2}{\sum_{x=1}^{N} \left(O_x - \overline{O}\right)^2}$$

2. Mean Absolute Error (MAE)

$$MAE = \frac{1}{N} \sum_{x=1}^{N} |P_x - O_x| \tag{3}$$

3. Relative Root Mean Square Error (RRMSE)

$$RRMSE = \left(\frac{RMSE}{\frac{1}{N} \sum_{x=1}^{N} P_x} \right) \tag{4}$$

Where

$$RMSE = \sqrt{\frac{1}{n} \sum_{x=1}^{n} (O_x - P_x)^2} \times 100\%$$

Where O is the actual value; P is the computed values; $\overline{O}$ is the average of Actual value; N is the number of data points.

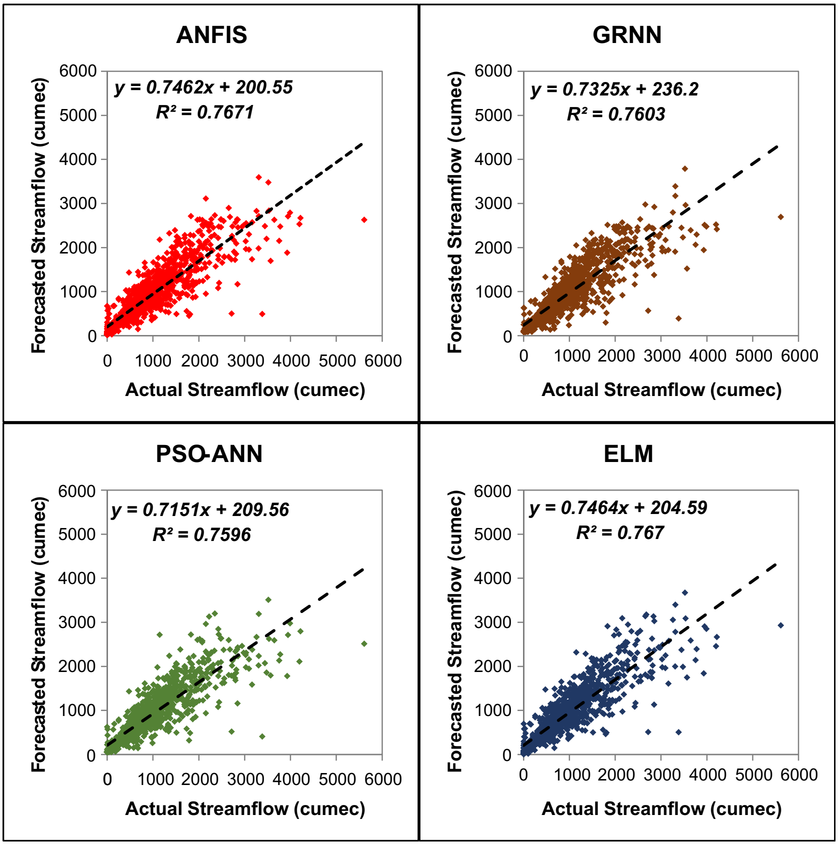

Fig. 3 Scatter plots for Model 1 showing one-day ahead streamflow forecast using IMD Rainfall Data for different soft-computing techniques in testing phase

4 Results and Discussion

4.1 IMD Rainfall Data

Table 2 shows the results wherein IMD Rainfall data is served as inputs, and Fig. 3 display the scatter plots for different soft-computing techniques of Model 1. The model comprises of present-day rainfall and streamflow as inputs, and one-day ahead

Table 2 Model performance with IMD Rainfall as inputs

Model	1: $R_t + S_t \rightarrow S_{t+1}$				2: $R_{t-1} + R_t + S_{t-1} + S_t \rightarrow S_{t+1}$			
	ANFIS	GRNN	PSO -ANN	ELM	ANFIS	GRNN	PSO -ANN	ELM
NNSE	0.809	0.806	0.801	0.810	0.737	0.802	0.765	0.807
MAE (m^3/s)	212.895	222.341	212.385	213.586	226.158	228.551	227.870	216.817
RRMSE	0.485	0.491	0.498	0.485	0.597	0.497	0.554	0.489

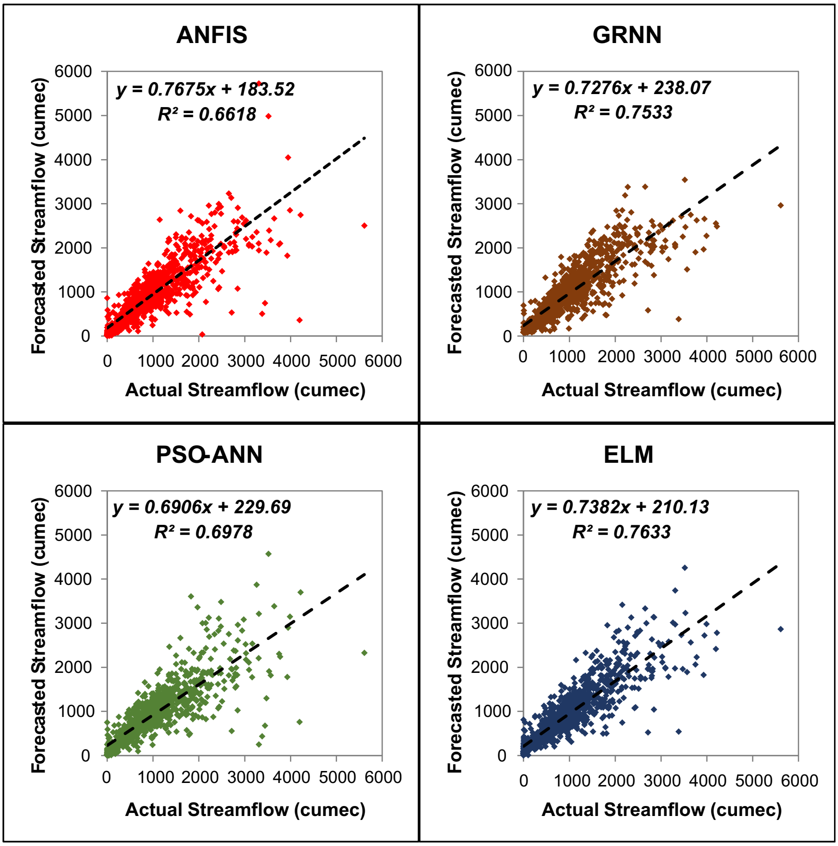

Fig. 4 Scatter plots for Model 2 showing one-day ahead streamflow forecast using IMD Rainfall Data for different soft-computing techniques in testing phase

streamflow as output. The table and figure it is seen that the statistical indices like R^2, NNSE and RRMSE is nearly the same and effective for ANFIS and ELM. The scatter plots infer that model shows robust performance in predicting lower range values for all techniques.

The scatter plots for different soft-computing techniques of Model 2 are shown in Fig. 4. In this model, present day and one-day lagged rainfall and streamflow values are considered as inputs, and one-day ahead streamflow is forecasted. The ELM

Table 3 Model performance using CHIRPS rainfall as inputs

Model	$1{:}R_t + S_t \rightarrow S_{t+1}$				$2{:}R_{t-1} + R_t + S_{t-1} + S_t \rightarrow S_{t+1}$			
	ANFIS	GRNN	PSO-ANN	ELM	ANFIS	GRNN	PSO-ANN	ELM
NNSE	0.825	0.813	0.813	0.825	0.788	0.803	0.813	0.824
MAE (m^3/s)	211.121	214.359	215.809	210.821	215.634	226.394	222.724	211.054
RRMSE	0.46	0.479	0.48	0.46	0.518	0.495	0.48	0.462

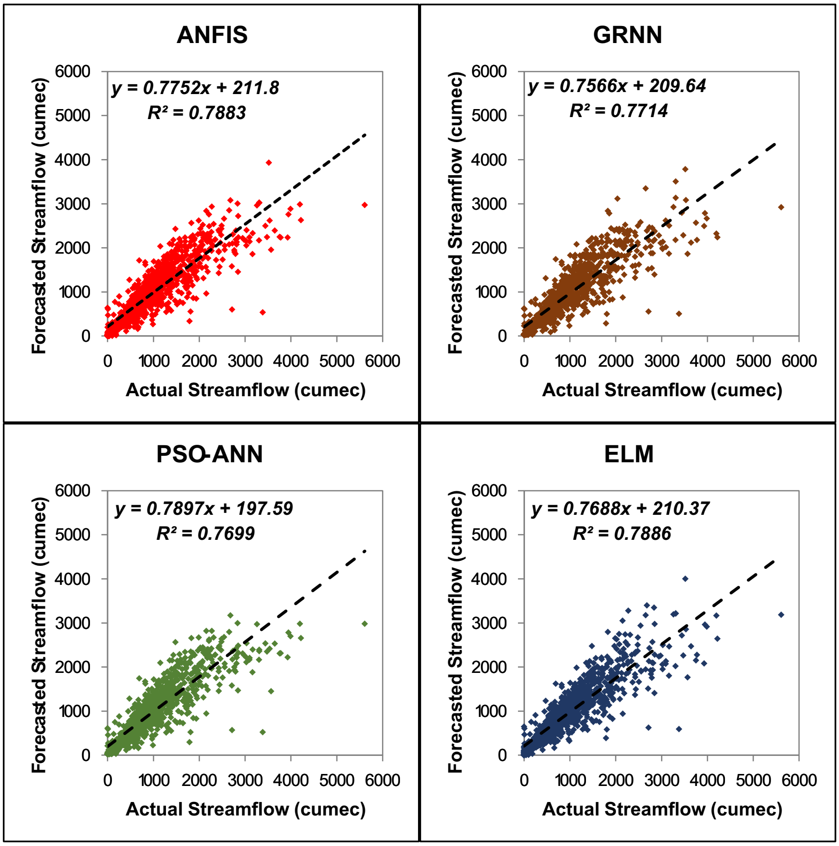

Fig. 5 Scatter plots for Model 1 showing one-day ahead streamflow forecast using CHIRPS Rainfall Data for different soft-computing techniques in testing phase

model performs better than ANFIS and PSO-ANN. The NNSE and RRMSE of ELM and GRNN are nearly same, but ELM stands more effective by exhibiting less MAE.

4.2 CHIRPS Rainfall Data

The model performance using CHIRPS rainfall data as inputs are presented in Table 3, and the scatter plots for Model 1 is shown in Fig. 5. From the table and figure it is seen that the statistical indices like R^2, NNSE and RRMSE is nearly the same and effective for ANFIS and ELM. The scatter plots infer that model shows robust performance in predicting lower range values for all techniques. The GRNN and PSO-ANN underperform in forecasting streamflow, but both the models have similar statistical indices.

The scatterplots for Model 2 with CHIRPS rainfall data as inputs is shown in Fig. 6. The ELM model performs better than ANFIS, GRNN, and PSO-ANN. The NNSE and RRMSE of ELM and PSO-ANN are nearly the same, but ELM stands more effective exhibiting higher determination coefficient ($R^2 = 0.787$).

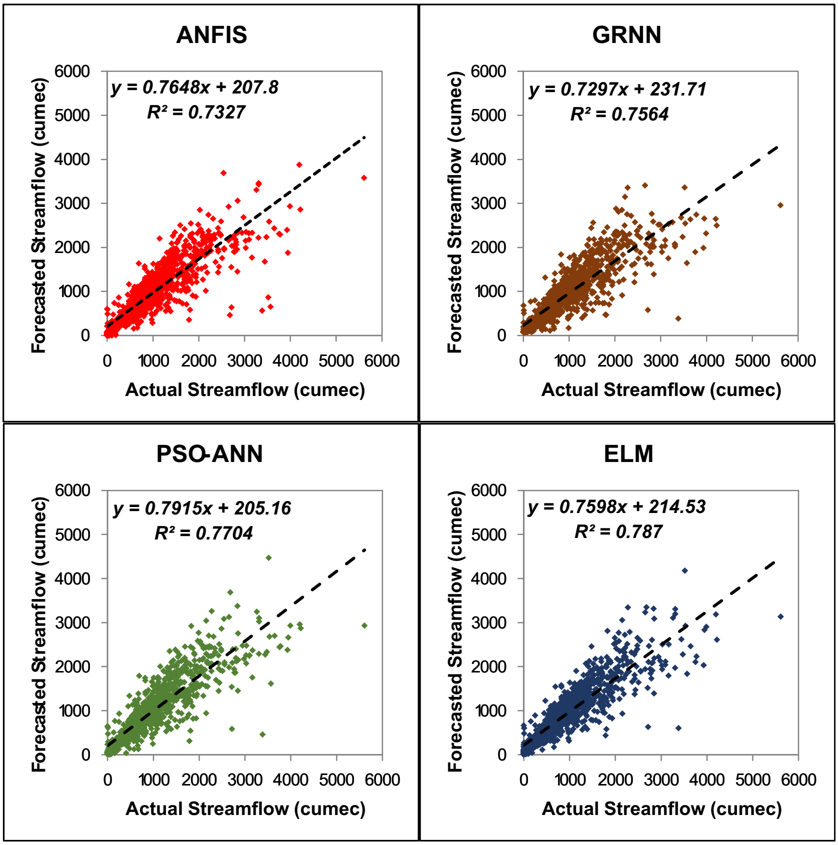

Fig. 6 Scatter plots for Model 2 showing one-day ahead streamflow forecast using CHIRPS Rainfall Data for different soft-computing techniques in testing

4.3 Comparison between IMD and CHIRPS Rainfall Model Performance

Taylor diagrams in Fig. 7 shows the relative performance of interpolation methods in forecasting the streamflow for IMD and CHIRPS rainfall models. In IMD Rainfall Model 1 it is seen that with present-day rainfall and streamflow as input parameters, the correlation coefficient, standard deviation, and RMSD perform nearly same for ANFIS, GRNN, PSO-ANN and ELM in forecasting streamflow. Whereas, in CHIRPS rainfall PSO-ANN has a higher variation than ANFIS, ELM, and GRNN.

IMD Rainfall Model 2 the inputs are rainfall and streamflow in a combination of one-day lagged and present-day respectively. The testing output shows that ANFIS and PSO-ANN underperform when compared with Model 1, whereas GRNN and ELM perform nearly the same. In CHIRPS rainfall model 2, the performance of ELM is superior when compared with ANFIS, GRNN, and PSO-ANN. The efficiency of ANFIS and PSO-ANN is increased drastically with the aid of CHIRPS rainfall data. It infers that the performance of GRNN and ELM models does not get much affected by lagging the input variables in case of IMD rainfall model. However, there is a slight deviation of values in CHIRPS rainfall data. The behavior of ELM remains nearly the same in all the combinations, irrespective of the datasets used.

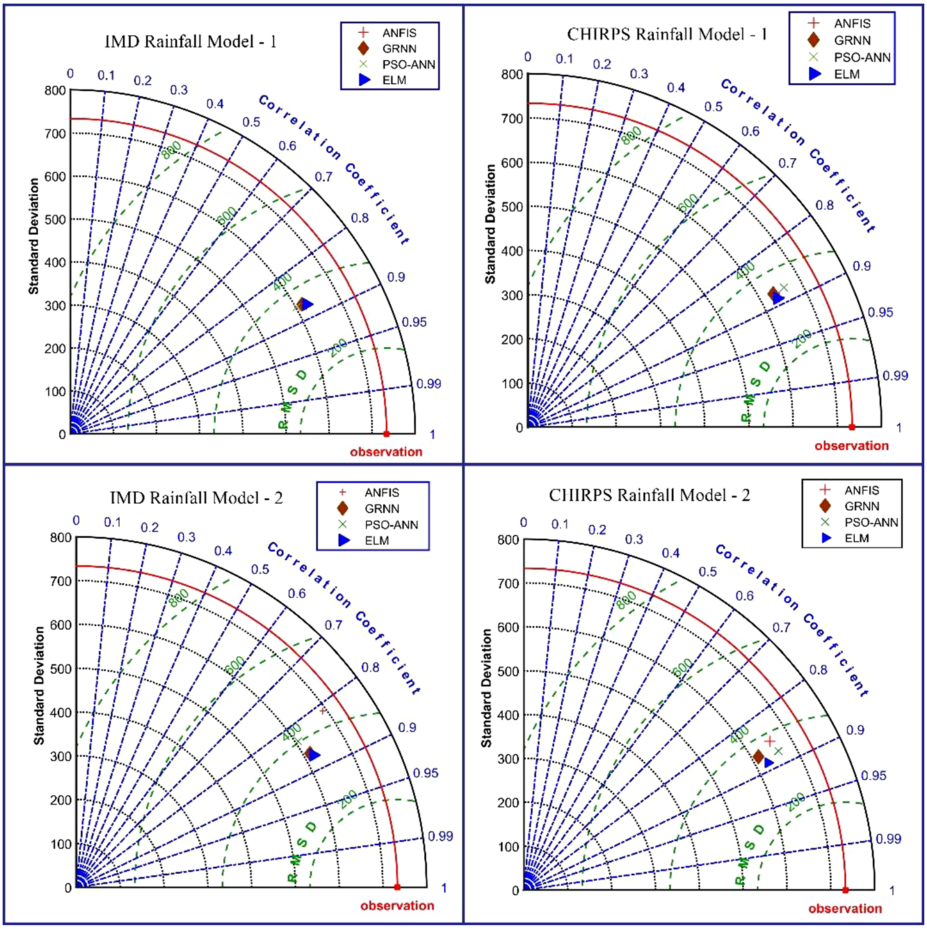

Fig. 7 Taylor Diagrams of Model 1 and Model 2 for both CHIRPS Rainfall data and IMD Rainfall data

5 Conclusions

The current research aims to evaluate the potential of CHIRPS rainfall data to forecast one-day ahead streamflow using soft-computing techniques like ANFIS, GRNN, PSO-ANN, and ELM over tropical wet climate, with Nethravathi Basin, Karnataka, India as an example. The effectiveness of CHIRPS rainfall models was compared with the IMD rainfall models for flow forecasting. The main findings of this research can be summarised as follows: The CHIRPS rainfall data was a useful alternative to the IMD Rainfall data for forecasting streamflow in the tropical wet environment of the Nethravathi Basin. There was a decrease in ANFIS model performance due to one-day lagged rainfall and streamflow values in the input combination of IMD rainfall data. The ELM algorithm potentially improves the accuracy of prediction in the modeling process compared to ANFIS, GRNN, and PSO-ANN. The future scope corresponds to the application of these algorithms to assess the potential of CHIRPS rainfall data over other climatic regions to forecast stream-flow.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

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