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RESEARCH ARTICLE

# River flow modeling for flood prediction using machine learning techniques in Godavari river, India

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## Abstract

Floods are highly impactful natural calamities, inflicting significant damage to infrastructure and causing numerous fatalities. These devastating events occur when rivers exceed their capacity or breach their banks due to intense precipitation.

Forecasting river flow in the minimum Godavari river basin of eastern India allowed researchers to examine the potential of four data-driven techniques, including the artificial neural network (ANN), support vector machine (SVM), nonlinear autoregressive network with exogenous input (NARX) and Gaussian process regression (GPR), and compare the outcomes to those of the proposed neuro-tree method. By combining values of the antecedent river flow from two gauging stations, various models were built utilizing the methodologies, and the results were compared to see which models had the best match. The performances of the generated models were examined using mean square error, coefficient of correlation (R), and Nash-Sutcliffe coefficient, three widely used statistical performance assessment metrics (NS).

An extensive analysis of the overall performance indicators revealed that the proposed neuro-tree algorithm models were more effective in flood prediction than the other four techniques employed in this study.

**Keywords:** Artificial neural network, Support vector machine, Nonlinear autoregressive network with exogenous input, Neuro-tree, Gaussian process regression.

## Introduction

The mathematical techniques used in physically complex models for flood forecasting require extensive calibration data, as well as some level of knowledge and experience (Aqil *et al.*, 2007). However, data-driven models are particularly useful for flood forecasting, which is primarily concerned with accurate flood forecasts, even if hydrological processes aren't fully understood (Nayak *et al.*, 2005). Recent examples of data-driven soft computing models that have emerged and gained popularity in the research community for solving computationally challenging problems include the artificial neural network (ANN), support vector machine (SVM), nonlinear autoregressive network with exogenous input (NARX) and gaussian process regression (GPR) (Misra & Shukla, 2019) (Keong *et al.*, 2016). In addition to handling noisy and uncertain data, these models have the ability to handle dynamic and nonlinear systems, enabling their use for disaster-related analysis and assessment when dataset uncertainty cannot be completely eliminated (Bachmair & Weiler, 2012; He *et al.*, 2014; Jang *et al.*, 1997; Kişi, 2006; Raghavendra. N & Deka, 2014; Rasmussen & Williams, 2006).

A back propagation neural networks (BPNN) has been used in (Jin *et al.*, 2010)to estimate the possibility of a flood disaster. To oversee optimal power generation in north-eastern Thailand, researchers in (Surussavadee & Wu, 2015)suggested a neural network-based wind forecast approach. An ANN based technique was also employed for river level forecasting using Bangladesh's Brahmaputra and Ganga rivers (Siddiquee & Hossain, 2015). The scientists also connected ANN with geographical information system (GIS) in order to study the region of India surrounding the tehri Reservoir's vulnerability to landslides (Kumar & Anbalagan, 2015). ANNs were also employed to anticipate the weather every day in Tiwi, Philippines (Sobrevilla *et al.*,

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2016). A unique combination of ANNs with the Internet of Things (IoT) using wireless sensor networks was presented for flood forecasting (Mitra *et al.*, 2016). One study also examined several ANN designs for rainfall prediction over India (Chakraverty & Gupta, 2008) nonlinear autoregressive network with exogenous Input (NARX) was used to forecast the hourly solar radiation and wind speed in Palermo, Italy (Firat & Güngör, 2008) and Mutah city, Jordan (Al-Sbou & Alawasa, 2017). SVM and GPR have recently become more well-known in this field.

SVM approach was utilized for flood vulnerability planning in Malaysia (Tehrany *et al.*, 2014) and Kayacik river, Turkey (Okkan *et al.*, 2014). The GPR technique was employed to calculate the river water in the Republic of Croatia's Drava river (Grbić *et al.*, 2013). In (Sun *et al.*, 2014), streamflow predictions for US river basins were performed using GPR one month in advance.

In order to model and predict floods in the minimum Godavari sub-basin in southeast India, this study aims to assess the efficacy and applicability of ANNs, support vector machines, nonlinear autoregressive networks with exogenous Input, and GPR, as well as to compare their results with those of the proposed Neuro-Tree method. The findings of these five data-driven models are obtained and compared in this research in order to assess their performance and determine how accurate they are at simulating river flow for flood forecasting.

## Methodology

Researchers have effectively used data-driven soft computing techniques in the discipline of calamity supervision because they strive to take advantage of data's tolerance for ambiguity, partial truth, and imprecision to provide reliable solutions(Pal *et al.*, 2004).

### *Neuro-Tree Algorithm*

The suggested Neuro-Tree technology combines two methodologies in a hybrid fashion. The suggested method combines Tree Bagger based on random forest with ANN. As depicted in Figure 1, the proposed technique is broken down into two parts. In step I, the backpropagation gradient descent algorithm is used to train an ANN with ten (10) neurons in the hidden layer. Stage II contains the tree bagger, which builds numerous trees from the subsets of samples from the ANN-provided data, receives the outputs from the trained network for the training dataset. The final forecast is then determined by averaging the projections from these sample trees.

Tree bagger technique is based on the random forest method, a non-parametric multivariate methodology based on machine learning algorithms. This approach consists of combining prediction trees that were each built using smaller samples of training data. Bag data is that which is not used in the creation of trees (OOB). At each model node, the optimum split is chosen randomly from a collection of predictors.

The proposed hybrid neuro-tree algorithm has several advantages over conventional regression methods which are:

- Hybrid approach to combine two techniques which gives better performance than ANNs.
- It gives better accuracy.
- It does not require any inherent knowledge about the statistical distribution of the underlying data.
- Prediction with the help of out-of-bag data helps avoid overfitting.
- It can handle noise in data.
- It can handle any non-linearity in the training dataset.
- It can also handle inconsistent and partial data.

### *Study Area*

In this research, a number of time series forecasting techniques are examined to determine their utility. The Godavari river in eastern India is used to demonstrate the applicability of these methodologies for time series forecasting and model design. The drainage area of the Godavari river is 312, 813 km$^2$, and its length is 1465 km. The Godavari river has a potential annual runoff of 110.54 km$^3$ (Dadhwal *et al.*, 2014). The Godavari river's position and drainage basin with the installation of daily flow recorders at the two river gauge stations on the main Godavari River branch, Bhadrachalam which is situated upstream of Polavaram are shown in Figure 2. This study utilizes both of these gauging stations' data sets to forecast river flow and floods.

### *Explanation of Data*

In comparison to ANN, NARX, ANFIS, SVM, and GPR, this study examined the performance of the suggested Neuro-Tree approach on daily flow. Data over 8 years, from 2013 to 2021, was taken for this study (India-WRIS WebGIS, n.d.)]. There were 2630 days in total for which the flow data was obtained (Central Water Commission (CWC) & Indian Space Research Organization (ISRO), 2022).

A training dataset made up of the years 2013 through 2020 and a testing dataset made up of the year 2021 were created from the data.

Table 1 displays the daily statistical factors for the river flow data, including the minimum value $M_{min}$, maximum

**Table 1:** Statistical parameters of the datasets

| | $M_{min}$ | $M_{max}$ | $M_{mean}$ | $M_{stdev}$ | $M_{ske}$ |
|---|---|---|---|---|---|
| Training | 34 | 47248.87 | 2931.43 | 5674.60 | 3.36 |
| Test | 154.8 | 827.01 | 340.14 | 115.98 | 0.63 |

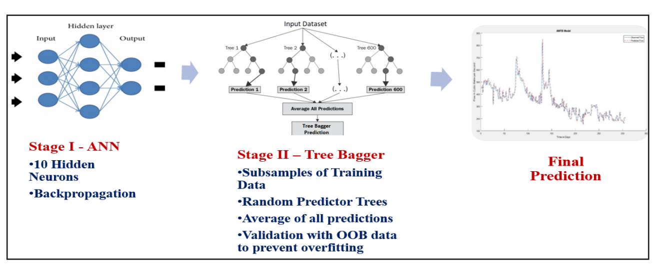


**Figure 1:** Neuro-tree algorithm architecture

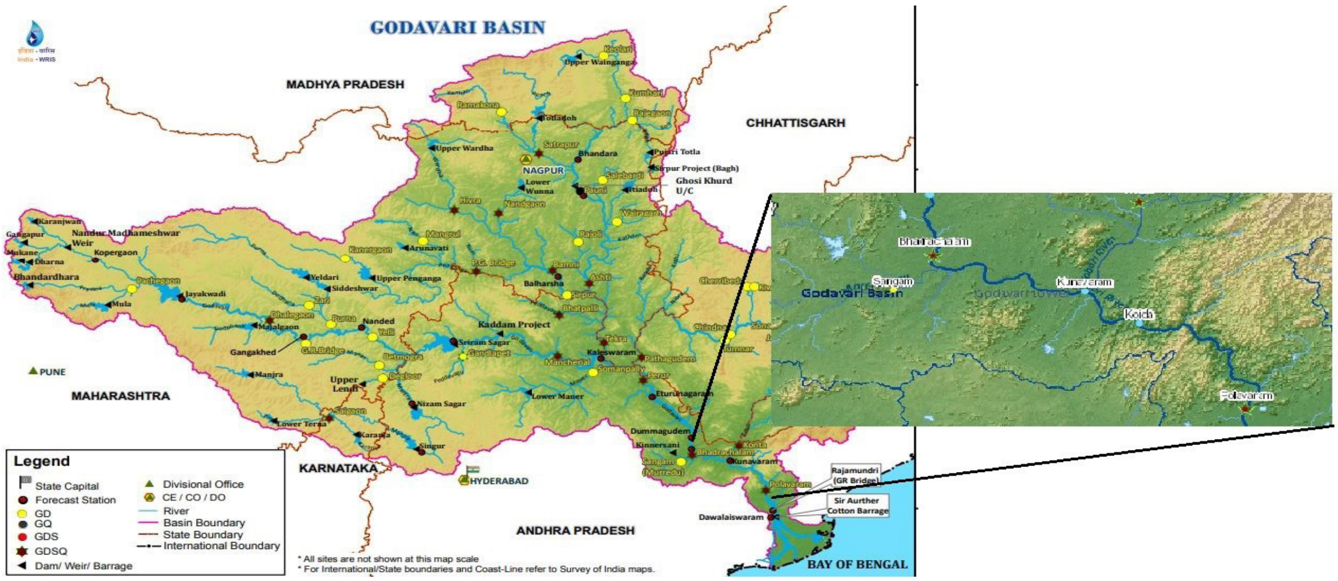


**Figure 2:** Location of Godavari River and the gauging stations

value $M_{max}$, mean $M_{mean}$, standard deviation $M_{stdev}$, and skewness coefficient $M_{ske}$.

### *Data Preprocessing*

The raw data collected from the source is first processed by normalizing them into a range between 0 and 1. The data must be standardized in order to provide effective and precise model training. Models trained on normalized data are said to perform better and converge more quickly, according to (Shanker *et al.*, 1996). The following equation is used in this study to normalize every data scaled in the scale of 0 to 1:

Where $X_{min}$ is the smallest value, $X_{max}$ is the highest value, X is the sample value, and X' is the normalized value.

### *Model Development*

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

The number of delays was determined using the partial auto correlation function (PCF) of the day-to-day stream data points at the Polavaram measuring site, as shown in Figure 3. The chart clearly shows how significantly the first three lags affect $M_{t+1}$.

For flow data with a latency of up to three days, Figure 4 is cross correlation between the Polavaram and Bhadrachalam gauging demonstrates a significant link. The first, third, and fourth lags of the Bhadrachalam measuring location and Polavaram's t-1, t-2, t-3, and t-4 were all inputs to the model in this investigation. Table 2 displays the forecasting model structures, with t+1 representing the flow at the end of the forecasting period. The five techniques mentioned above are then applied on these data models developed above to obtain predictions. The efficiency and accuracy of these models and techniques are tested through the use of various model performance metrics and criteria.

### *Criteria of Models Performance*

Four widely used statistical performance evaluation criteria were used to evaluate the models proposed for this article. Statistics were created using the correlation coefficient, commonly referred to as regression (R), nash-sutcliffe efficiency coefficient (NS), and mean square error (MSE). MSE

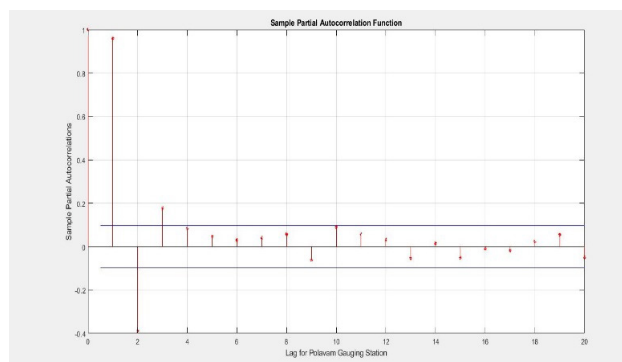


**Figure 3:** Partial auto-correlation of day-to-day stream data of Polavaram

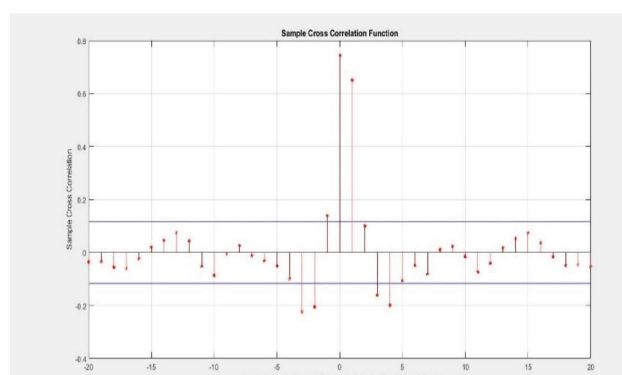


**Figure 4:** Cross-correlation of day-to-day stream data of Polavaram and Bhadrachalam stations.

determines a model's prediction propensity, R determines the linear relationship strength, and the predictive ability of the model is determined by NS.

The calculation of MSE is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - a_i)^2$$

n denotes the dataset's size, ai denotes the model's output, and ti denotes the resultant real output. R is considered as the association between goals and outcomes. If R takes the value 1, it denotes a close association between the targets and outputs, however when it is 0 or 1, it denotes a random relationship.

The equation is given as:

$$R = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(a_i - \bar{a})}{\sqrt{\sum_{i=1}^{n}(t_i - \bar{t})^2 \sum_{i=1}^{n}(a_i - \bar{a})^2}}$$

It is possible to compute the NS as follows:

$$NS = 1 - \frac{\sum_{i=1}^{n}(t_i - a_i)^2}{\sum_{i=1}^{n}(t_i - \bar{t})^2}$$

where, n denotes the amount of the dataset, $a_i$ denotes the model's yield, and $t_i$ denotes the reliable real output. A model is supposed to produce a flawless forecast if the NS criteria is equal to 1, but as shown in , an accurate model has an NS value larger than 0.8 (Shu & Ouarda, 2008).

## Results

The models developed above were evaluated by applying ANN, NARX, SVM, Neuro-Tree and GPR methods, and the results are presented in this section. A MATLAB 2017b environment was used for implementing and analyzing the above-mentioned techniques.

**Table 2:** Models of Forecasting Structures

| *Number of Model* | *Input* | *Result* |
|---|---|---|
| I | $P_{t-1}$ | $P_{t+1}$ |
| II | $P_{t-1}P_{t-2}$ | |
| III | $P_{t-1}P_{t-2}P_{t-3}$ | |
| IV | $P_{t-1}B_{t-1}$ | |
| V | $P_{t-1}P_{t-2}B_{t-1}$ | |
| VI | $P_{t-1}P_{t-2}P_{t-3}B_{t-1}$ | |
| VII | $P_{t-1}B_{t-3}$ | |
| VIII | $P_{t-1}P_{t-2}B_{t-3}$ | |
| IX | $P_{t-1}P_{t-2}P_{t-3}B_{t-3}$ | |
| X | $P_{t-1}B_{t-4}$ | |
| XI | $P_{t-1}P_{t-2}B_{t-4}$ | |
| XII | $P_{t-1}P_{t-2}P_{t-3}B_{t-4}$ | |
| XIII | $P_{t-1}B_{t-1}B_{t-3}$ | |
| XIV | $P_{t-1}B_{t-1}B_{t-3}B_{t-4}$ | |
| XV | $P_{t-1}P_{t-2}B_{t-1}B_{t-3}$ | |
| XVI | $P_{t-1}P_{t-2}B_{t-1}B_{t-3}B_{t-4}$ | |
| XVII | $P_{t-1}P_{t-2}P_{t-3}B_{t-1}B_{t-3}$ | |
| XVIII | $P_{t-1}P_{t-2}P_{t-3}B_{t-1}B_{t-3}B_{t-4}$ | |

### *Artificial Neural Networks*

The ANN models were trained using the Levenberg-Marquardt and Bayesian regularization backpropagation algorithms. Model 1 with 10 hidden neurons is the best fit model for the ANN when training a Bayesian regularization algorithm on a single antecedent flow dataset from Polavaram gauging. It has the minimum MSE value of 0.00509, a maximum R value of 0.911, and the minimum NS value of 0.8282. Figure 5 displays a visualization of the ANN Model 1's observed and computed fluctuations in flow.

### *Neuro-Tree*

*NARX*

A NARX network with 10 hidden neurons and input delays of two-time steps was used to train the models. NARX models are trained using the Levenberg-Marquardt method, and the outcomes are contrasted. Model 2 with the first two antecedent flow data from Polavaram gauging station which has the minimum MSE value of 0.00581, maximum R value of 0.900, and maximum NS value of 0.8014, determined to be the best fir NARX model. The estimated and observed flow variations for the NARX Model 2 are depicted in Figure 6.

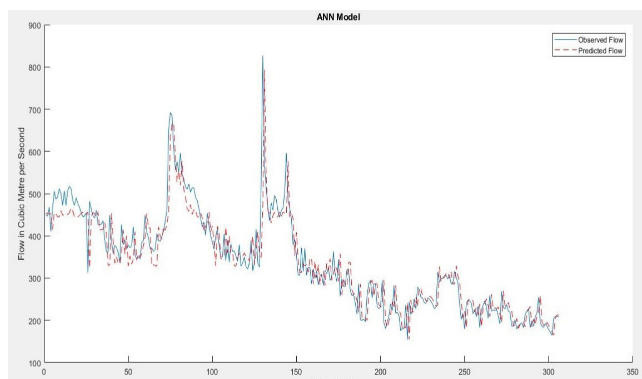


**Figure 5:** By contrasting Model 1 with ten (10) hidden neurons during testing and subsequently training with the Bayesian regularization algorithm, it is possible to examine the difference between observed and predicted flow.

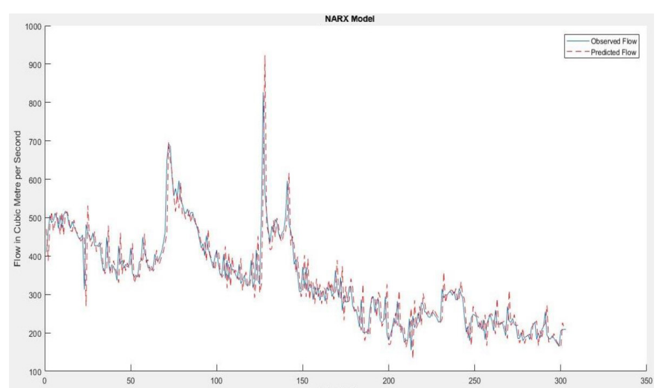


**Figure 6:** Testing Model 2 against NARX predicted flow obtained from the observed data.

*SVM*

The performance indices from each of the 18 models were compared using the SVM approach. Model 1 would be the best fit for SVM if it includes just one antecedent flow measurement from the Polavaram gauging station, according to analysis using the minimum MSE of 0.00473, the maximum R value of 0.923, and the maximum NS value of 0.8405. Figure 7 displays a visualization of the SVM model 1's observed and computed fluctuations in flow.

The proposed Neuro-Tree technique was employed to all 18 the models. The ANN stage was trained with 10 neurons in the hidden layer with Levenberg Marquardt algorithm. The findings from the ANN stage were transferred to the Tree Bagger stage, where 1000 trees were created for each model with a minimum leaf size of 5, and the performance indices attained were evaluated. The results are shown in

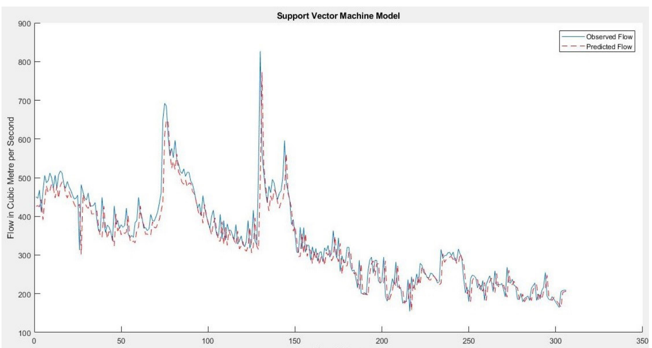


**Figure 7:** Testing model 1 against SVM predicted flow obtained from the observed data.

**Table 3:** Neuro-Tree models' performance indices

| *Models* | *MSE* | *R* | *NS* |
|---|---|---|---|
| I | 0.00475 | 0.917 | 0.8398 |
| II | 0.00467 | 0.938 | 0.8427 |
| III | 0.00489 | 0.914 | 0.8350 |
| IV | 0.10300 | 0.213 | 0.7230 |
| V | 0.73398 | 0.911 | 0.1158 |
| VI | 0.03433 | 0.579 | 0.4603 |
| VII | 0.21420 | 0.717 | 0.3021 |
| VIII | 1.48133 | 0.524 | 0.1863 |
| IX | 1.34783 | 0.237 | 0.3806 |
| X | 0.46650 | 0.712 | 0.2185 |
| XI | 0.42499 | 0.607 | 0.4258 |
| XII | 0.58625 | 0.273 | 0.3126 |
| XIII | 0.41069 | 0.505 | 0.2893 |
| XIV | 0.16691 | 0.282 | 0.5683 |
| XV | 0.11081 | 0.099 | 0.5860 |
| XVI | 0.08710 | 0.297 | 0.4628 |
| XVII | 0.45743 | 0.441 | 0.4883 |
| XVIII | 0.45514 | 0.438 | 0.3872 |

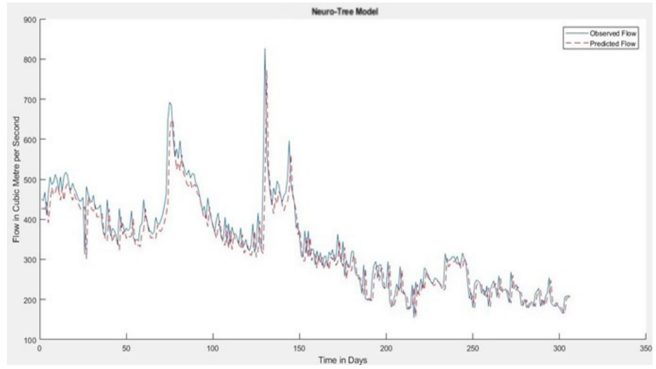


**Figure 8:** Testing Model 2 against Neuro-Tree predicted flow obtained from the observed data.

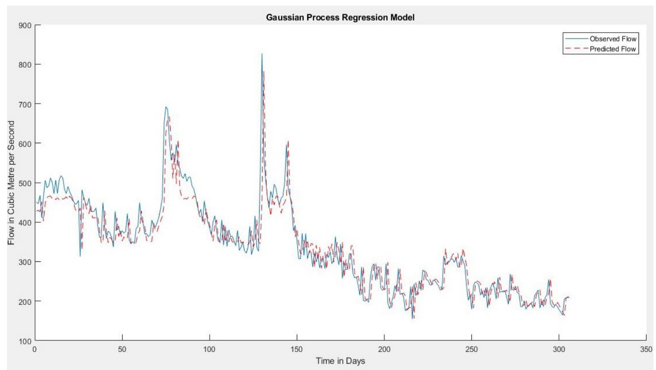


**Figure 9:** Testing Model 1 against GPR predicted flow obtained from the observed data.

Table 3. Model 2 would fit Neuro-Tree the best if the first two precursor flow data from Polavaram station were included. This was determined using the minimum MSE of 0.00467, the maximum R value of 0. 938, and the maximum NS value of 0. 8427. Figure 8 displays a visualization of the observed and calculated flow variations of the Neuro-Tree model 2.

**GPR**

The GPR technique was used to compare the performance indices from each of the 18 models. Using Model 1, which had the lowest MSE of 0.00499, highest R of 0.913, and highest NS of 0.8317, would be the best match for GPR if it included on one antecedent flow data from Polavaram gauging station. The observed and calculated flow fluctuations for the GPR model 1 are depicted in Figure 9.

**Table 4:** Modeling comparison of ANN, NARX, SVM, NEURO-TREE and GPR

| *Algorithm* | *Model* | *MSE* | *R* | *NS* |
|---|---|---|---|---|
| ANN | I | 0.005090 | 0.9110 | 0.82820 |
| NARX | II | 0.005890 | 0.9000 | 0.80140 |
| SVM | I | 0.004730 | 0.9230 | 0.84050 |
| Neuro-Tree | II | 0.004670 | 0.9380 | 0.84270 |
| GPR | I | 0.004990 | 0.9130 | 0.83170 |

## Discussion

The performances of best fit models of ANN,NARX, SVM, GPR, and Neuro-Tree techniques are shown in Table 4.

It can be observed from the results that Neuro-Tree model seem to perform better than other models as it has minimum MSE and highest R and NS values, followed by SVM, GPR, ANN and NARX models. All models depicted good prediction for low values of river flow but only ANN, SVM and GPR models were able to maintain their accuracy for higher value of river flow. The NARX overestimated the peak flow while SVM, Neuro-Tree and GPR underestimated the peak flow value.

The Neuro-Tree, SVM, GPR, ANN and NARX could provide accurate and reliable flood forecasts and good forecasting performance. It can be observed from the results that the proposed Neuro-Tree algorithm proved superior to other algorithm in flood and river flow forecasting.

## Conclusion

We compared ANN, NARX, SVM, and GPR models for forecasting floods with the Neuro-Tree method proposed in this research. To achieve this goal, a case study on the Godavari river gauging stations at Polavaram and Bhadrachalam was conducted in eastern India. The performance of all examined and evaluated models, including ANN, NARX, SVM, and GPR, was best demonstrated by Neuro-Tree, which also showed the greatest R and NS values and the lowest MSE values. Thus, the Neuro-Tree model may be more accurate than ANNs, NARXs, SVMs, and GPRs. This study shows the Neuro-Tree technique has better flood prediction performance than the other methods.

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