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Rainfall-runoff modelling using soft computing techniques for various watersheds of Madhya Pradesh, India

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ABSTRACT: The main study was the estimation of runoff using present day and previous days rainfall and previous days runoff as a daily input variable using artificial neural networks (ANNs) and wavelet-based ANNs (WANNs). Rainfall-runoff data were collected, standardized, and selected as inputs using the Gamma test. The methodology for runoff estimation and modeling using ANNs and WANNs was applied to the regions of Narsimhpur and Mandla in Madhya Pradesh. As the number of neurons was increased, the correlation between rainfall and runoff was initially improved and then reduced. Therefore, an optimum number of neurons was identified at which the best correlation was achieved. Better correlation coefficients, least root mean square errors, higher Nash-Sutcliffe efficiency, and greater Willmott indices were obtained for WANNs models compared to ANNs models. These results can be utilized for runoff forecasting.

Keywords: Artificial Neural Networks (ANNs), Nash Shutcliff coefficient of efficiency, Wavelet

Water is considered the main component of elements for living beings. It is acknowledged as a major component of the hydrosphere. The hydrosphere is defined in terms of the occurrence, circulation, and distribution of water. The processes through which water is vaporized from surface sources and living organisms are known as evaporation and transpiration. After vaporization, water is condensed into the atmosphere and circulated in the form of clouds, leading to precipitation or rainfall.

Latterly, significant focus has been directed toward the study of runoff and its spatial and temporal variations. An urgency has been recognized for the development of an effective soil and water management system to address challenges posed by water scarcity and natural disasters such as floods and landslides. Rainfall-runoff modeling has been recognized as a suitable tool for runoff prediction, enabling the implementation of protective actions anti phenomena like floods (Singh *et al.*, 2022).

In recent decades, the accurate modeling of runoff has been actively pursued by researchers in hydrology due to its significance in water resource planning, water power generation, urban planning, irrigation, and other meteorological applications.

Vast datasets and complex environmental computations have been required by conceptual and physical models. Because of the nonlinear nature of the rainfall-runoff process and the complexity of physical models, intelligent models have been employed. However, inconsistent or illogical results have occasionally been generated when nonlinear hydrological systems were modeled.

Notably, nonlinear artificial neural networks (ANNs) have been utilized for the successful prediction of hydrological time series (Mirzania *et al.*, 2021). To simulate river flow from catchments, atmospheric, dynamic, and static models are incorporated within hydrological modeling frameworks. The precision of hydrologic modeling is vastly concerned by the characteristic of data. Therefore, difficulties are encountered in model simulation when data availability is limited. Physical flow measurements are considered infeasible within the spatiotemporal domain, and in such cases, river flow simulation is supported through soft computing techniques (Rathnayake *et al.*, 2023). Runoff is recognized foremost complex and critical phenomena in the hydrological cycle. For its modeling, multiple perspectives have been introduced to enhance the development and refinement of predictive models.

Cognitive computing has been engaged to reliably model hydrological processes (Saravani *et al.*, 2023). Rainfall-runoff modeling has been enhanced to improve streamflow prediction through the use of more accurate data and modeling techniques, which are deliberated indispensable for effective water control and overflow risk mitigation. Rainfall-runoff modeling has been computed using machine learning and conceptual models (Daif *et al.*, 2025). Coordinated water resource planning has been defined as a process in which water, land, and associated resources are developed and managed equitably without compromising sustainability. Computational tools ranging from simple lumped models to complex distributed watershed models have been introduced, and soft computing and inferential methods have been implemented to address water resource challenges. Composite models have been perceived to perform superiority in various studies. However, variation in prediction accuracy and uncertainty has been reported across models. A universally best-performing model has not been recognized, as effectiveness is determined by the characteristics of the data applied (Rosamma, 2022).

Floods have been categorized among the most destructive natural disasters, and modeling complexities have been encountered. Flood anticipatory models have been evolved to reduce risk, provide policy insights, minimize human loss, and mitigate property damage. Over the past two decades, key input has been created by machine learning methods to replicate the complex physical processes of floods mathematically, offering enhanced performance and cost-efficient solutions. The growing popularity of machine learning among hydrologists has been attributed to its vast benefits and applications. More accurate and efficient models have been pursued through the proposal of novel machine learning methods and the hybridization of existing ones. Key trends such as hybridization, data decomposition, algorithm ensembles, and model optimization have been reported as influential in improving flood prediction models. This reconsideration has been perspective as a guideline for hydrologists and climate scientists in selecting

suitable machine learning methods aligned with the prediction task (Mosavi *et al.*, 2018). Within catchments, significant impacts on land productivity have been perceived due to changes in streamflow, which affect soil moisture retention and nutrient availability through usually desiccating and rinsing cycles. To anticipate prospective adapt and delve into the influence of different eventuality, cognitive computing have been employed lately in the water field for streamflow simulation (Gharbia *et al.*, 2022). Severe and devastating consequences are caused by flooding across the globe; an increase in the frequency and severity of these events is expected due to climate change. Advances in flood modeling and prediction methods, along with developments in open-source data and computing capabilities, have made flood modeling methods more accessible. However, a challenge is posed by the diversity in modeling approaches and available data sources when determining approach the most suited to a study area (Ramsamy, 2022).

MATERIALS AND METHODS

Narsimhpur has been identified as a watershed through which the Narmada River flows across Madhya Pradesh. This watershed is located between 22°54' 59.993 N latitude and 79°09' 26.003 E longitude. The Narmada River is believed to originate from the Amarkantak Plateau in the Anuppur district of Madhya Pradesh. A total length of 1,312 kilometers has been attributed to the Narmada River. In the region traversed by the river, the catchment area of the Narsimhpur watershed has been measured at 5,125.55 square kilometers. An elevation of 347 meters (1,138 feet) prior datum has been recorded for the watershed. Warm season temperatures have been noticed to range from 45°C to 46°C, while during colder periods, temperatures drop to approximately 9°C. The rainy season in this watershed is noted to occur from June to September. During the monsoon, an average rainfall of 40 inches is received. The culturable command area (CCA) of this catchment area has been described to be 131,925 hectares. Mandla is situated between 22°36' 0.003 N latitude and 80°22' 48.003 E longitude. The watershed area has been measured at 8,771 square

kilometers. An elevation of 539 meters (1,768 feet) prior datum has been registered. During summer, temperatures are observed to range from 25°C to 45°C. The rainy season in Mandla is understood to begin in June and continue through September. In winter, temperatures are found to range from 11°C to 21°C. An average annual rainfall of 1,427.7 millimeters has been reported. The culturable command area of Mandla has been estimated at 14,000 hectares.

To achieve optimum and efficient training between input and output data, all data were systematized using a standard normal variable (z). Simple and rapid training convergence within a narrow range was enabled during model development. Dimensionality was eliminated, allowing equal weightage to be assigned to all variables. The standard normal variable has been defined as:

$$Z = (x - \mu)/\sigma \quad \dots(1)$$

Where, μ is mean of the observed variable and σ is standard deviation of observed variable.

Wavelets used in continuous wavelet transforms (CWTs) are governed by the uncertainty principle derived from Fourier analysis and sampling theory: the simultaneous precise assignment of time and frequency to a signal event is not permitted. A lower bound is possessed by the uncertainty product of time and frequency. Consequently, events are represented as entire regions in the time-scale plane in a scaleogram, rather than as singular points. Discrete wavelet bases are also interpreted in accordance with other uncertainty principles.

The discrete wavelet transform has been acknowledged for operating with reduced computational complexity, requiring only $O(N)$ time, in contrast to the $O(N \log N)$ time required by the fast Fourier transform (FFT). This advantage is attributed not to the transform itself, but to the use of logarithmic frequency division—unlike the FFT, which is founded on evenly spaced frequency divisions using discrete Fourier transform (DFT) basis functions.

This complexity consideration is applicable only

when the filter size is not directly associated the signal size. A wavelet lacking compact support, including the Shannon wavelet, would necessitate $O(N^2)$ operations. It is worth mentioning a logarithmic Fourier Transform is also available with $O(N)$ complexity, although logarithmic sampling in time is required—making it suitable only for specific signal types.

Data compression is typically carried out using an approximation to the Discrete Wavelet Transform (DWT), assuming prior signal sampling. Signal analysis is commonly conducted using the CWT. The DWT approximation is employed in engineering and computer science, while the CWT is utilized in scientific research. Data transformation and encoding have been accomplished through wavelet transforms, enabling efficient compression.

RESULTS AND DISCUSSION

A total of 14 model provided were developed with varying hidden layer size to examine the impact of attribute of input variability on model performance. The optimal numerous sensory neurons in the hidden layer were also investigated, ranging from 3 to 42—for example, 6-3-3-1, 6-6-6-1, 6-9-9-1, 6-12-12-1 up to 6-42-42-1. These configurations represent single-layered neural network and a pair of hidden layers neuron counts. The neuronal density in the hidden layers was increased in intervals of 3 (from 3 to 42), while the input layer maintained a constant 6 neurons. The maximum permitted number of neurons was reached for each of the 14 models. For runoff estimation using the ANN model, each model was operated by dissevering the input and output data into 70% for training and 30% for testing. The runoff function is defined by Equation (2) using rainfall and runoff from previous days. Based on the findings Gamma test, the input combination consists of present-day rainfall, previous one-day rainfall, and runoff from the previous three days.

$$Q_t = f(R_t, R_{t-1}, R_{t-2}, R_{t-3}, Q_{t-1}, Q_{t-2}) \dots(2)$$

Artificial neural network models for Narsimhpur

The best models for training and testing are shown in Table 4.4. After best practice analysis the

prediction performance of all models, it can be displayed that ANN-6 having architecture (6-18-18-1) showed the enhanced performance during training having minimum value of RMSE (0.9061 cumec), maximum value of correlation coefficient ($r = 0.82$), maximum value of NSCE (0.90), PARE divergent from -0.9×10^{-3} , upmost value of WI (0.80) and MAE varied from 1.1. The values for training and testing of RMSE, correlation coefficient, NSCE, PARE, WI and MAE varied from 0.9061 cumec to 1.104 cumec., 0.82 to 0.90, 0.90 to 0.70, -0.9×10^{-3} to -0.42×10^{-3} , 0.80 to 0.82 and 1.1 to 1.1 respectively. Negative value of PARE showed under-anticipated and positive value of PARE showed over-anticipated.

ANN-06 with architecture (6-36-36-1) showed minimum PARE value of -0.42×10^{-3} . Fig. 4.1 showed an under-predicted model for testing as observed and predicted runoff values represented to be in close agreement.

ANN model for Mandla

The best models for training and testing are shown in Table 4.6. After best practice analysis prediction performance of all models, it can be revealed that ANN-06 having architecture (6-18-18-1) showed the enhanced performance of all during training having minimum value of RMSE (0.849 cumec), supreme value of correlation coefficient ($r = 0.80$), uttermost

Table 1: Key performance indicators for ANN (training and testing) based runoff prediction models of Narsimhpur

Model	Architecture	Training						Testing					
		RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
ANN-01	6-3-3-1	1.0190	0.78	0.80	-3.2	0.70	4.1	1.1327	0.80	0.60	-1.2	0.80	5.1
ANN-02	6-6-6-1	0.9300	0.76	0.82	-3.3	0.72	4.5	1.1607	0.82	0.63	-2.1	0.81	5.2
ANN-03	6-9-9-1	0.9900	0.77	0.83	-3.1	0.73	4.3	1.218	0.83	0.64	-2.3	0.83	5.3
ANN-04	6-12-12-1	0.9300	0.78	0.88	-3.0	0.74	4.6	1.246	0.88	0.67	-2.4	0.82	5.4
ANN-05	6-15-15-1	1.0190	0.73	0.85	-2.5	0.75	3.2	1.274	0.85	0.78	-2.5	0.88	5.6
ANN-06	6-18-18-1	0.9061	0.82	0.90	-0.9	0.80	1.1	1.104	0.90	0.70	-0.42	0.82	1.1
ANN-07	6-21-21-1	1.1327	0.75	0.86	-1.2	0.79	2.1	1.1327	0.86	0.72	-0.56	0.80	1.2
ANN-08	6-24-24-1	1.1609	0.77	0.87	-1.3	0.77	2.3	1.1609	0.87	0.77	0.28	0.79	1.3
ANN-09	6-27-27-1	1.2740	0.80	0.88	-1.1	0.78	2.4	1.189	0.88	0.76	-2.1	0.77	1.4
ANN-10	6-30-30-1	1.2460	0.72	0.86	-1.2	0.76	2.5	1.218	0.86	0.72	-2.2	0.76	3.1
ANN-11	6-33-33-1	1.2180	0.73	0.85	0.80	0.74	2.6	1.246	0.85	0.71	-2.3	0.77	3.2
ANN-12	6-36-36-1	1.1890	0.70	0.88	0.56	0.75	3.2	1.189	0.88	0.68	-3.1	0.80	2.5
ANN-13	6-39-39-1	1.1327	0.73	0.82	-1.2	0.72	3.3	1.1609	0.82	0.69	-3.2	0.81	3.6
ANN-14	6-42-42-1	1.1607	0.76	0.81	-3.2	0.75	3.4	1.1327	0.81	0.67	-4.1	0.77	4.1

Table 2: Key performance indicators for ANN (training and testing) based runoff prediction models of Mandla

Model	Architecture	Training						Testing					
		RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE	RMSE (cumec)	r	NSCE	PARE (10^{-3})	WI	MAE
ANN-01	6-3-3-1	1.019	0.70	0.62	-2.1	0.60	2.1	1.1327	0.80	0.80	-4.2	0.70	2.1
ANN-02	6-6-6-1	1.048	0.72	0.63	-2.3	0.62	2.3	1.1609	0.81	0.82	-4.3	0.71	2.5
ANN-03	6-9-9-1	1.076	0.73	0.64	-3.1	0.63	2.5	1.189	0.82	0.80	-2.2	0.72	2.6
ANN-04	6-12-12-1	0.963	0.74	0.65	-3.2	0.64	2.6	1.218	0.83	0.81	-2.3	0.73	2.7
ANN-05	6-15-15-1	0.990	0.75	0.66	-3.3	0.65	2.7	1.246	0.84	0.82	-2.4	0.74	2.3
ANN-06	6-18-18-1	0.849	0.80	0.67	-0.9	0.72	1.2	0.849	0.89	0.83	-1.2	0.80	1.2
ANN-07	6-21-21-1	0.906	0.79	0.60	-2.5	0.69	2.3	0.9061	0.86	0.78	-1.3	0.79	1.3
ANN-08	6-24-24-1	0.877	0.78	0.58	-2.6	0.62	3.1	0.877	0.85	0.77	0.56	0.78	1.5
ANN-09	6-27-27-1	0.930	0.77	0.52	-2.7	0.63	3.2	0.963	0.84	0.73	0.28	0.77	1.3
ANN-10	6-30-30-1	0.963	0.76	0.55	0.50	0.65	3.3	0.99	0.86	0.77	0.26	0.75	4.1
ANN-11	6-33-33-1	0.990	0.73	0.53	0.28	0.64	4.1	1.019	0.77	0.79	0.90	0.76	4.2
ANN-12	6-36-36-1	1.019	0.72	0.60	0.82	0.62	4.8	1.048	0.78	0.77	-3.1	0.74	4.3
ANN-13	6-39-39-1	1.076	0.71	0.61	0.86	0.65	4.9	1.076	0.75	0.76	-3.2	0.73	2.3
ANN-14	6-42-42-1	1.104	0.70	0.63	-1.2	0.62	4.2	1.104	0.72	0.75	-4.2	0.75	2.2

value of NSCE (0.67), PARE value of -0.9×10^{-3} , upmost value of WI (0.72) and MAE value of 1.2. The values of RMSE, correlation coefficient, NSCE, WI, PARE and MAE varied from 0.849 cumec to 0.849 cumec., 0.80 to 0.89, 0.67 to 0.83, 0.72 to 0.80, -0.9×10^{-3} to -1.2×10^{-3} and 1.2 to 1.2, respectively. Fig 1 showed an under-anticipated model for training and testing as observed and anticipated runoff values represented to be in close agreement.

Wavelet neural network based runoff prediction models for Narsimhpur

The results of computational assessment for training and testing are presented in Table 3. The Table 3 shows the values of unparallel performance indicators for training and testing data which were used for nomination of the best runoff anticipated model. It can be observed for training data values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE ranged from 0.651, 0.93, 0.89, 0.80, 2.1 and 0.80×10^{-3} . It can be deduced that model WANN-06 having architecture (6-18-18-1) showed the best

performance having minimum value of RMSE (0.651 cumec), maximum value of correlation coefficient (0.93), maximum value of NSCE (0.89), maximum value of WI (0.80), minimum value of MAE (2.1) and minimum PARE value of 0.80×10^{-3} . For testing data, model 6 given best values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE varied from 0.9061, 0.84, 0.73, 0.73, 2.1 and -1.5×10^{-3} .

WANN based runoff prediction models for Mandla

The results obtained during training and testing are presented in Table 4. The Table 4 displayed the values of enhanced performance indicators for

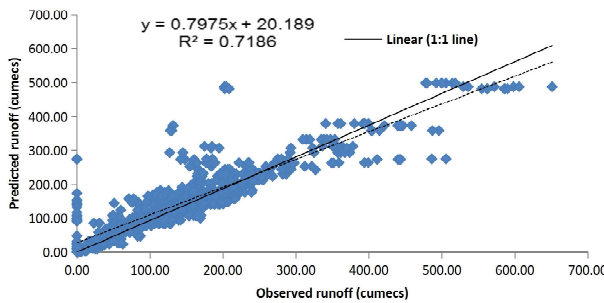


Fig. 1: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during training period for Narsimhpur

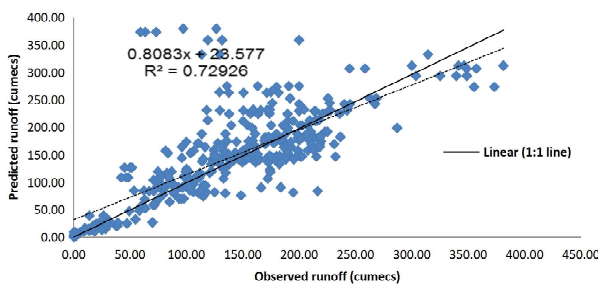


Fig. 2: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during testing period for Narsimhpur

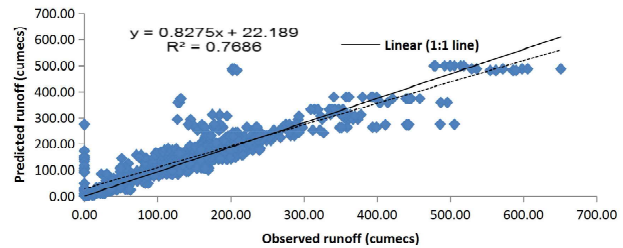


Fig. 3: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during training period for Mandla

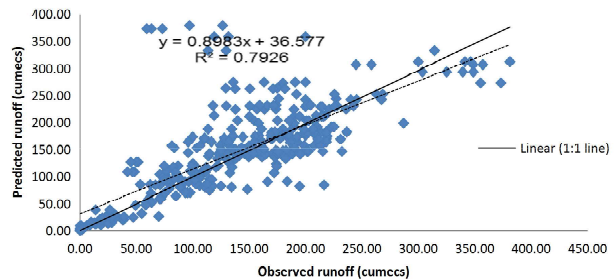


Fig. 4: Scatter plot of predicted and observed runoff for ANN-06 (6-18-18-1) model during testing period for Mandla

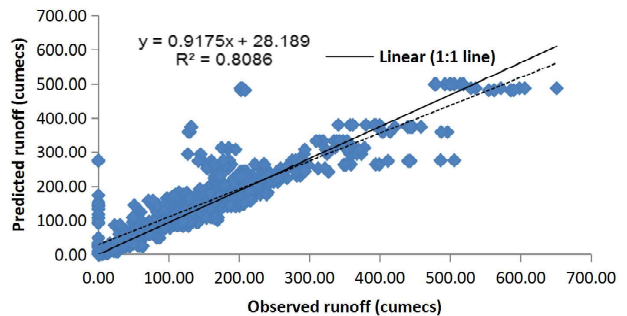


Fig. 5: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during training period for Narsimhpur

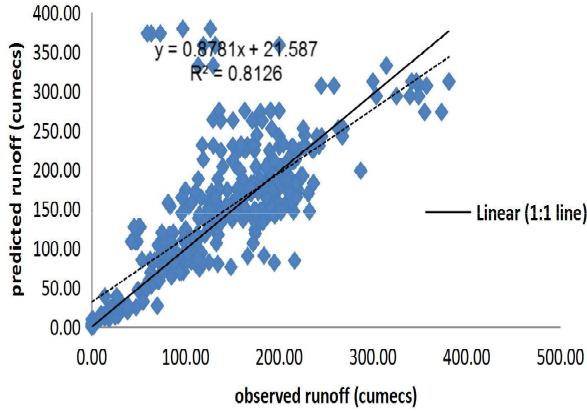


Fig. 6: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during testing period for Narsimhpur

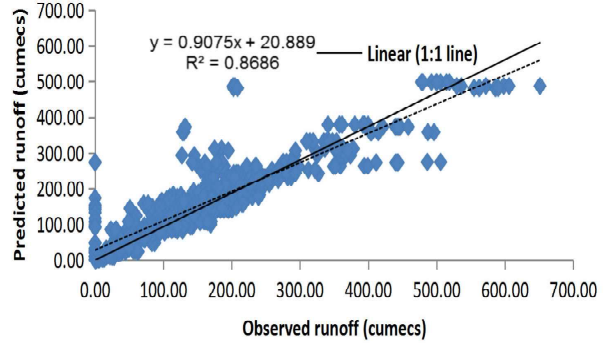


Fig. 7: Scatter plot of predicted and observed runoff for WANN-06 (6-18-18-1) model during training period for Mandla

Table 4: Key performance indicators for WANN (training and testing) based on runoff prediction models of Narsimhpur

Model	Architecture	Training						Testing					
		RMSE (cumecc)	r	NSCE	PARE (10 ⁻³)	WI	MAE	RMSE (cumecc)	r	NSCE	PARE (10 ⁻³)	WI	MAE
WANN-01	6-3-3-1	0.793	0.92	0.80	-7.8	0.80	7.1	1.019	0.80	0.69	-5.4	0.72	6.1
WANN-02	6-6-6-1	0.821	0.91	0.82	-7.2	0.82	7.2	1.048	0.79	0.70	-5.3	0.73	6.2
WANN-03	6-9-9-1	0.849	0.92	0.83	-7.3	0.72	7.3	1.076	0.77	0.71	-2.4	0.71	6.3
WANN-04	6-12-12-1	0.990	0.89	0.86	-7.1	0.73	7.8	1.104	0.73	0.72	-2.3	0.70	6.4
WANN-05	6-15-15-1	1.019	0.88	0.88	-2.1	0.83	7.3	0.963	0.77	0.70	-3.4	0.69	1.2
WANN-06	6-18-18-1	0.651	0.93	0.89	0.80	0.80	2.1	0.9061	0.84	0.73	-1.5	0.73	2.1
WANN-07	6-21-21-1	0.679	0.90	0.82	-2.3	0.76	2.2	1.104	0.82	0.70	-5.2	0.66	3.1
WANN-08	6-24-24-1	0.707	0.89	0.83	-3.2	0.75	3.2	1.076	0.80	0.62	-5.3	0.67	3.2
WANN-09	6-27-27-1	0.736	0.88	0.80	-3.3	0.74	3.3	1.1327	0.76	0.63	0.56	0.65	3.3
WANN-10	6-30-30-1	0.765	0.86	0.77	-3.4	0.72	4.5	1.1609	0.74	0.64	-3.2	0.66	3.4
WANN-11	6-33-33-1	0.793	0.87	0.79	-3.2	0.73	4.6	1.189	0.75	0.65	-3.1	0.67	3.5
WANN-12	6-36-36-1	0.821	0.88	0.77	-3.1	0.71	4.4	1.1327	0.76	0.66	-3.0	0.65	2.1
WANN-13	6-39-39-1	0.849	0.85	0.75	-3.0	0.70	4.3	1.189	0.77	0.67	-3.3	0.63	2.2
WANN-14	6-42-42-1	0.906	0.86	0.86	-4.1	0.75	4.5	1.104	0.73	0.62	-3.6	0.70	2.1

Table 5: Key performance indicators for WANN (training and testing) based on runoff prediction models of Mandla

Model	Architecture	Training						Testing					
		RMSE (cumecc)	r	NSCE	PARE (10 ⁻³)	WI	MAE	RMSE (cumecc)	r	NSCE	PARE (10 ⁻³)	WI	MAE
WANN-01	6-3-3-1	0.849	0.80	0.77	-2.1	0.73	5.1	1.133	0.92	0.82	-3.1	0.77	4.3
WANN-02	6-6-6-1	0.906	0.82	0.76	-2.3	0.72	5.4	1.218	0.93	0.83	-3.3	0.76	4.5
WANN-03	6-9-9-1	0.877	0.83	0.73	-2.4	0.71	5.3	1.246	0.90	0.81	-3.5	0.80	4.3
WANN-04	6-12-12-1	1.019	0.81	0.75	-2.5	0.70	5.6	1.274	0.91	0.80	-3.8	0.79	4.2
WANN-05	6-15-15-1	0.930	0.82	0.74	-2.3	0.69	3.2	1.189	0.90	0.82	-3.9	0.77	4.3
WANN-06	6-18-18-1	0.793	0.85	0.79	-1.1	0.77	2.1	1.104	0.94	0.85	-0.80	0.82	4.1
WANN-7	6-21-21-1	0.821	0.80	0.77	-1.2	0.76	2.5	1.133	0.91	0.82	-0.90	0.81	2.1
WANN-08	6-24-24-1	0.906	0.79	0.75	-1.3	0.75	3.5	1.189	0.90	0.80	0.56	0.79	2.3
WANN-09	6-27-27-1	0.877	0.77	0.76	-3.1	0.74	3.3	1.161	0.89	0.81	0.28	0.77	2.5
WANN-10	6-30-30-1	0.930	0.76	0.72	-3.3	0.73	3.2	1.133	0.88	0.82	0.26	0.75	3.1
WANN-11	6-33-33-1	0.906	0.74	0.73	-3.4	0.72	3.7	1.274	0.82	0.83	-3.5	0.76	3.5
WANN-12	6-36-36-1	0.930	0.75	0.70	-2.1	0.71	3.8	1.303	0.83	0.80	-3.6	0.72	4.2
WANN-13	6-39-39-1	0.963	0.77	0.71	-2.2	0.70	3.6	1.330	0.85	0.81	-2.1	0.73	4.5
WANN-14	6-42-42-1	0.930	0.76	0.72	-2.3	0.72	4.5	1.359	0.86	0.82	-2.2	0.72	4.6

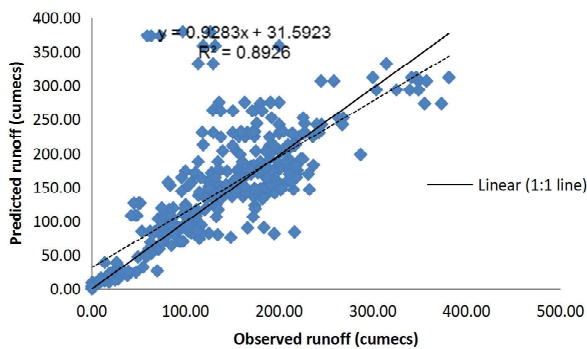


Fig. 8: Time series and scatter plots of predicted and observed runoff for WANN-06 (6- 18-18-1) model during testing period for Mandla

training and testing data which were used nomination of the runoff anticipated model. It can be observed for training and testing data values of RMSE, correlation coefficient, NSCE, WI, MAE and PARE varied from 0.793 to 1.104, 0.85 to 0.94, 0.79 to 0.85, 0.77 to 0.82, 2.1 to 4.1 and $1.1 \cdot 10^{-3}$ to $-0.80 \cdot 10^{-3}$. The analysis indicates that model WANN-06 having architecture (6-18-18-1) showed the best performance having utmost value of RMSE (1.104 cumec), uttermost value of correlation coefficient (0.94), maximum value of NSCE (0.85), maximum value of WI (0.82), supreme value of MAE (4.1) and value of PARE ($1.1 \cdot 10^{-3}$).

CONCLUSION

Water resources are affected by parts of the atmosphere, lithosphere, and hydrosphere, including both living and non-living organisms on Earth. As water availability across the planet varies by location and time, it has been studied by researchers due to the limited quantity of pure water present. The quantity of water available on Earth is currently being placed under heavy stress due to high demand and limited availability. Sustainable water management is required to ensure that the gap between demand and supply of water resources is narrowed.

In the present work, runoff generated by rainfall was estimated using various approaches for functional analysis. Rainfall and corresponding runoff data spanning 12 years (2010–2021) for Narsinghpur and

Mandla were collected during the monsoon season (June, July, August, and September) from the Water Resource Information System website. Runoff data (in cumec) and rainfall data (in mm) were obtained. A Gamma test was conducted to recognize the optimal data combinations for the enhancement various rainfall-runoff models. Input variables were selected as rainfall at time t , rainfall at time $t-1$, runoff at time $t-1$, runoff at time $t-2$, and runoff at time $t-3$. Runoff at time t was considered as the output.

Optimum results for model development and validation were provided by the ANN model with the architecture 6-18-18-1. Similarly, optimum results for both training and testing were achieved by the WANN model with the same architecture. On average, better correlation coefficients, lower mean square errors, and reduced pooled average relative errors were yielded by WANN models. Additionally, higher Nash–Sutcliffe efficiency and greater Willmott index values were obtained in comparison to ANN models. These outcomes can be utilized for runoff forecasting across various applications such as irrigation, flood control, and related water management strategies.

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