

Prediction of run-off considering land use and land cover management practices and ground slope using artificial neural networks

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Abstract

The objective of this investigation is to choose the hydro-meteorological (precipitation and run-off) study by using Artificial Neural Networks (ANNs) in the district Bankura. ANNs model is applied for general impact of different climatic variables, for precipitation, land use and land cover, drainage density and slope of catchment [1-2]. Bankura located on Lower Gangetic Plain (Zone-III), India. The examinations have accumulated the real time data series for the most recent 120 years (1901-2020) for the six referenced meteorological stations of Bankura [3-4]. For predicting the ANNs model, the open data were separated as 70% considered as training purpose, 15% in the field of testing, and 15% utilized during validation. The model display with further developed Nash-Sutcliffe Efficiency (NSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and the outcome shows acceptable more than 97%.

Key words: Run-off, ANNs modelling, Climate change, Hydro-meteorological data, Topography.

1. Introduction

Changes in land cover and land management practices have been observed as critical factors behind changes in hydrological systems, which cause a difference in runoff such as frequency of peak flow, volume of discharge [5]. Land use may have a substantial impact on stream flow, which may be degraded as human activities increase [6-7].

Relationships between land use and surface water quality are relevant topics for discussion as human activities increase in a watershed [8-9]. As more land cover changes to impervious Land Use Land Cover (LULC), the hydrologic cycle is affected by increasing storm runoff, reducing vegetation cover, and increasing transport of sediment to streams, which may further impact water quality [10-11]. Land use and land cover, and hydrologies are interrelated but land use changes have significant impact on global water output. The quality of evapotranspiration, infiltration and surface runoff that happens during and after rainfall event directly influenced by LULC). These variables influence the water yields of surface stream and ground water aquifers [12]. Humans are the main cause for altering the natural environment through agriculture; deforestation, urbanization, and land use land [13].

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2. Study area

The region Bankura is situated in Lower Ganges basin and eastern slant of Chhota Nagpur plateau under Drought Prone Area Programme (DPAP) 2008. They have plainly referenced 7 blocks in Bankura region named water scant region.

Bankura district is arranged somewhere in the range of $22^{\circ}38'00''$ and $23^{\circ}38'00''$ N latitude and $86^{\circ}36'00''$ and $87^{\circ}46'00''$ E longitude. It has an area of 6882 square kilometres. North and north-east of the district is limited by East and West Bardhaman region from which it is isolated generally by the Damodar River. On the south-east it is limited by Hooghly district, on the south by Paschim Midnapur area and on the west by Purulia district. Bankura district has been depicted as the interfacing join between the plains of Bengal on the east and Chhota Nagpur Level on the west. Toward the west the surface continuously rises given approach to undulating nation, blended with rocky hillocks.

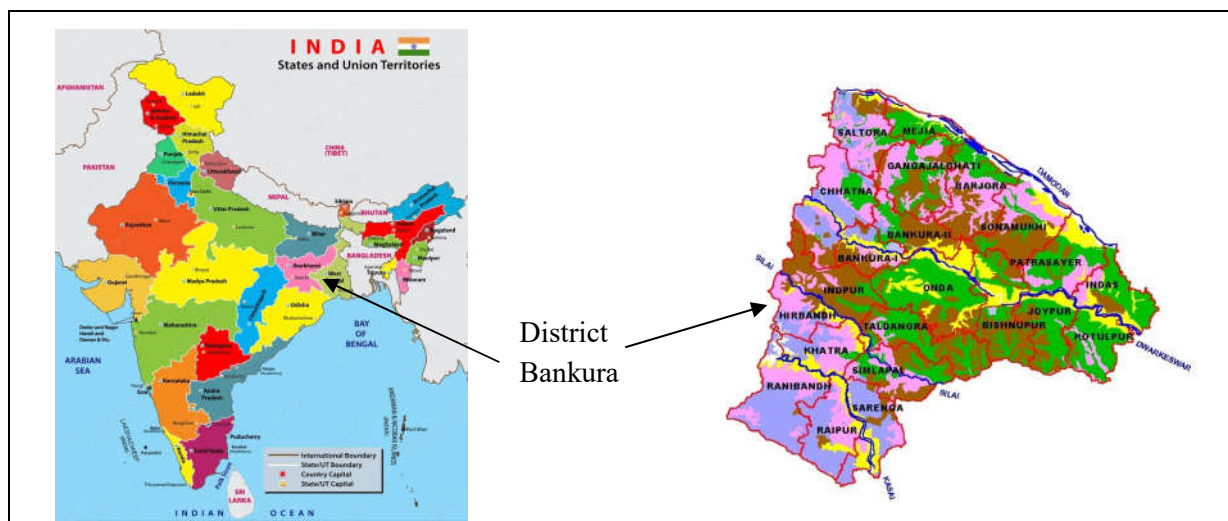


Figure 1. Study area location map of district Bankura.

(<https://stock.adobe.com/>, <https://bankura.gov.in/maps/>, accessed on 12-07-2023) [14]

3. Data collection

In this study, the researcher collected the secondary data (meteorological data) from India Meteorological Department, Pune from 1901 to 2020. In this study, information has been gathered from India Meteorological Division, Pune, for six meteorological stations situated in the area Bankura like i) Bankura, ii) Bankura (CWC), iii) Joypur, iv) Kangsabati dam, v) Ranibandh, vi) Indus. The accompanying five factors are rainfall, average temperature, land use and land cover, drainage density and slope of catchment. In the current examination, the pattern of rainfall intensity is utilized having three distinct kinds of intensity for example 30mm/hour, 60mm/hour and 90mm/hour.

3.1 Land Use and Land Cover (LULC)

Land Use details of the district Bankura are 59.54 % cultivation, 12.36% cultivable wasteland, 8.48% barren land, and 19.61% cover with forest. The land utilization pattern of

the district reveals that Saltora, Mejia, Gangajalghati, Bankura, Bishnupur, and Patrasayer all have more than 57% of land under cultivation. The Joypur block has the highest cultivation (66%) whereas India has 83.01% highest cultivation. All these blocks are located in the central and eastern parts of the district. In the western and south-western part of the district have a less cultivated area. In Chhatna, Ranibandh and Raipur have more than 30% barren land and other 30% cover by forest. The percentage is covered by the forest of the following blocks – Barjora 23%, Ranibandh 32.87%, Taldangra 31.00%, and Bishnupur 35%. Researchers have collected the all land use data from Soil and Land Use Survey of India, Pusa, New Delhi.



Figure 2. Details of forest map of the district Bankura.

(District Survey Report, July, 2018, Ministry of Environment, Govt. of India)

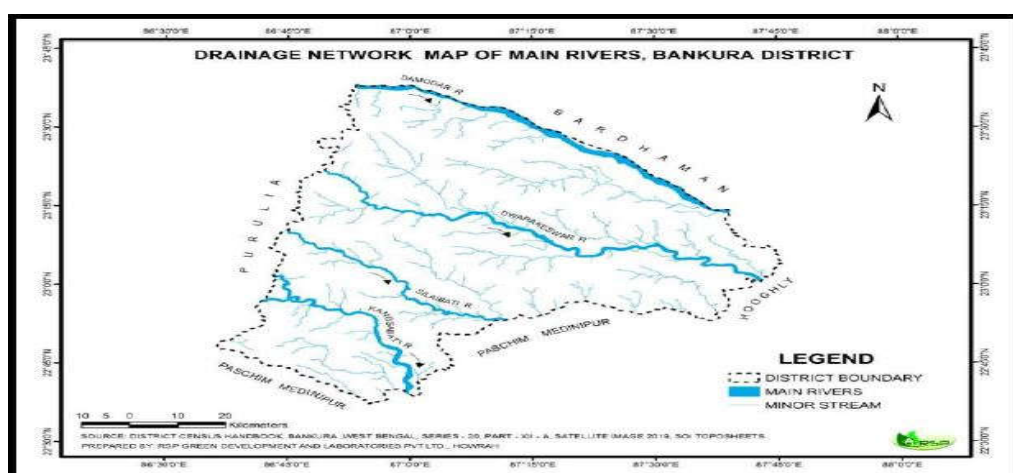


Figure 3. Details of drainage network map of the district Bankura.

(District Survey Report, July, 2018, Ministry of Environment, Govt. of India)

3.2 Slope details

The land of the district Bankura consists of nine slope categories. The slopes of the district according to their area are as per table no-8. In the present investigation, three different overland slopes of 1%, 2%, and 3% were used.

Table 1. Classification of slope according to their area of district Bankura.

(Sources: Soil and Land Use Survey of India, Pusa, New Delhi)

Sl no	Slopes classes	Area in hectare	Area in percentage (%)
1.	Level slope	23614.00	3.430
2.	Level – Very Gently slope	371351.00	53.960
3.	Very Gently slope	669.00	0.100
4.	Very Gently – Gently slope	238513.00	34.660
5.	Gently – Moderately slope	6301.00	0.920
6.	Strongly– Moderately steep slope	8088.00	1.180
7.	Moderately steep – Steep slope	1561.00	0.230
8.	Steep – Very steep slope	995.00	0.140
9.	Miscellaneous slope	37108.00	5.390
Total		688200.00	100.000

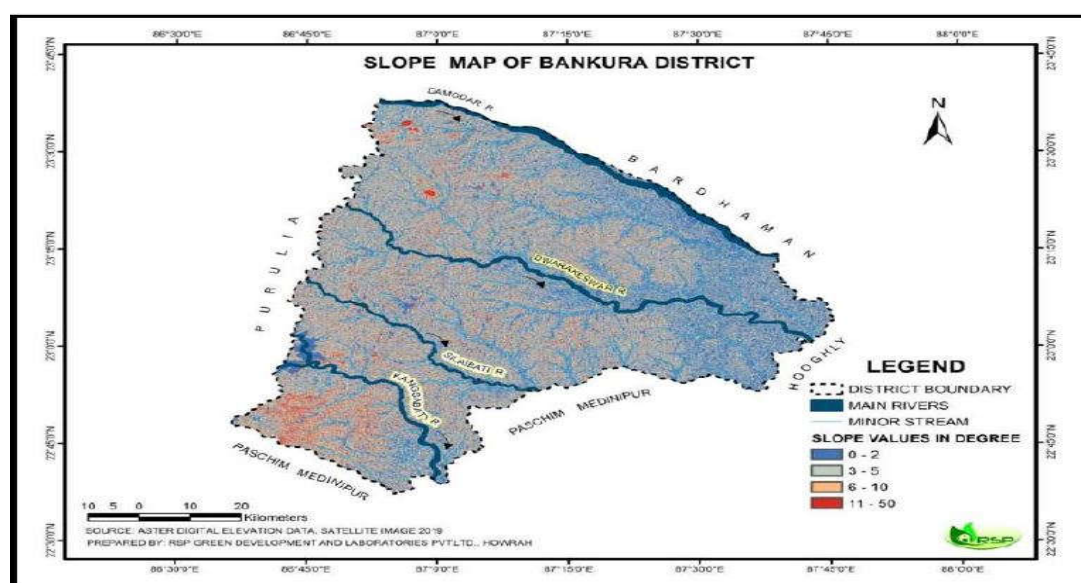


Figure 4, details slope map of the district Bankura.

(Source: District Survey Report, July, 2018, Ministry of Environment, Govt. of India.)

4. Materials and method

The research has been used the equation of [15-16] which is more suitable for Lower Gangetic Basin, district Bankura, West Bengal. This equation is recommended by the International Water Management Institute (IWMI) in working Paper-130 which is published

in 2008 [17]. Simultaneously this is also recommended by the National Institute of Hydrology, Roorkee, India in 2008. The equation is as follows:

$$R_m = \frac{F_v^{0.49} (P_m - 0.5T_m)}{26.5} \quad (1)$$

Where, R_m = Annual mean runoff in cm, P_m = the average annual rainfall in cm, T_m = the average annual temperature in $^{\circ}\text{C}$, and F_v = vegetal cover factor.

$$F_v = \frac{(a_1 F_F + a_2 F_G + a_3 F_A + a_4 F_W)}{A} \quad (2)$$

Where, a_1, a_2, a_3, a_4 are the weighting factors, F_F is the percentage area of forest, F_G is the percentage area of grass and scrub land, F_A is the percentage area of arable land, and F_W is the percentage area of waste land only.

In Hydrological research, ANN is a perceived device to build a structure between multiple input factors and explicit results. This method is more appropriate for forecasting and runoff examination [18-20]. In this examination, ANNs comprise of five input layers, a single hidden layer, and an output layer. Hidden layers might be expanded if there should be an occurrence of a perplexing circumstance [21-23].

First and foremost, ANNs are prepared with a progression of noticed inputs informational collection viz. rainfall, average temperature, cloud cover, potential evapotranspiration, and relative humidity, indicated as X_1, X_2, X_3, X_4 , and X_5 individually and yield information, runoff signified as Y_i . In the preparation cycle, the coefficients (signified as W_k and W_{kj}) are acquired. The primary interaction completes investigation for the ideal nonlinear connection among input factors and result. In direct regression, the network includes input factors (X_j) linear functions worked by transfer function as displayed in Equation (1). Where, the hidden unit gets from every single input variable. We are composing numerically by the accompanying conditions:

$$U_K = \varphi \left(\sum_{j=i}^m W_{kj} X_j + b_{kj} \right) \quad (3)$$

$$Y_i = \varphi \left(\sum_{k=i}^l W_k u_k + b_k \right) \quad (4)$$

Where, $X_1, X_2, \dots, X_m$ are input factors; φ means the exaggerated exchange capability; $W_{k1}, W_{k2}, \dots, W_{km}$ and $W_1, W_2, \dots, W_k$ are the coefficients (loads) of the organization; $u_1, u_2, \dots, u_k$ signifies stowed away units; b_{kj} and b_k are the constants to straight relapse, and Y_i is the result signal. Secret unit straight capability along consistent gets last result of the organization as displayed in Equation (2). From the beginning, standardization of the information series is preceded according to condition (v) inside ± 1 .

$$P_{nor} = 2 \left(\frac{P_o - P_{min}}{P_{max} - P_{min}} \right) - 1 \quad (5)$$

In equation (5.29), P_o , P_{nor} , P_{min} , and P_{max} indicates observed data, standardized data, minimum observed data, and maximum observed data individually. During ANNs modeling, data series were arbitrarily circulated into training, testing, and validation in 70%/15%/15% configuration. At first, the network was prepared with training data series, and after that testing, data series was used to calibrate the behaving of prepared models. After calibration and testing finally, the data series was utilized to approve and to finish the ANNs model. While training the network, Gradient Descent (GD) algorithm was applied to lessen the network error by a function minimization routine and to further develop the network yield.

$$\text{Overall error } E_D = \sum (t_j - y_i)^2 \quad (6)$$

Where t_j = desired error and y_i = calculated output.

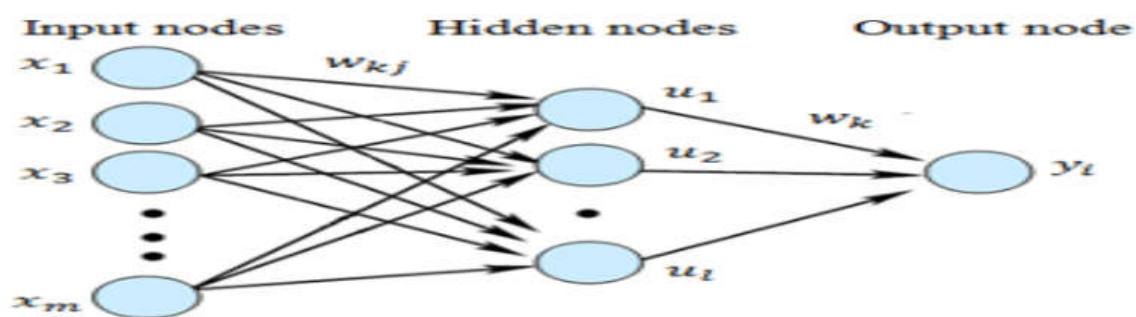


Figure 5. Schematic illustrations of Artificial Neural Networks with single hidden layer.

4.1 Nash-Sutcliffe Efficiency (NSE)

For assessing performance of the proposed model of the both districts, the Nash-Sutcliffe efficiency (NSE) is a significant measure that is communicated by the Equation (7).

$$\text{Nash-Sutcliffe Efficiency (NSE) in percentage (\%), } NSE = \left(1 - \frac{\sum_{i=1}^n (Y_o - Y_k)^2}{\sum_{i=1}^n (Y_o - Y_m)^2} \right) \quad (7)$$

Where, Y_o = Observed flow at time t , Y_k = Predicted flow (Kinematic flow) at time t , and Y_m = Mean observed flow.

Nash-Sutcliffe efficiency (NSE) measures the changeability of the model (Legates and McCabe 1999). NSE goes from $-\infty$ at a most pessimistic scenario to +1 for an ideal relationship. As indicated by Shamseldin 1997 [24], Dey et al. 2020 [25], the worth of NSE 0.9 or more is extremely palatable, 0.8 to 0.9 addresses a genuinely decent model and 0.8 is an unsuitable outcome. The efficiency of model 'M₃' is 97.49%, the best fitted model and very satisfactory for the district Bankura.

4.2 Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{k=1}^K (Q_k - \bar{Q}_k)^2}{K}} \quad (8)$$

Where, Q_k = Observed flow, $\bar{Q}_k$ = Predicted flow, and K = Total number of years considered (Validation data).

The worth of RMSE estimates the exactness of the model, and as least as could be expected. The worth of RMSE and MAE is pretty much comparable (close to about something very similar) and addresses a decent good model [1,2,26].

The value of Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for the district of Bankura are more or less similar i.e. 42.00 and 35.47 of model 'M₃' respectively.

4.3 Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{k=1}^K |Q_k - \bar{Q}_k|}{K} \quad (9)$$

Where, Q_k = Observed flow, $\bar{Q}_k$ = Predicted flow, and K = Total number of year considered (Validation data). The value of MAE measures the accuracy of the model and as minimum as possible [27-28].

4.4 Error in runoff computation

The error in Runoff for the present investigation was estimated by,

$$\text{Error in \% } e = \left(1 - \frac{Y_K}{Y_O}\right) * 100 \quad (10)$$

Where, Y_o = Observed Runoff, and Y_K = Predicted Runoff.

The error value in run-off computation estimates the precision of the model and is as lower as could really be expected.

5. Results and Discussion

Table 2. The result containing the ANNs model for the district of Bankura.

Model	Input parameters	Coefficients	Weights	Transfer Function	Discharge	
					Observed	Predicted
M ₁	Monthly Rainfall,	4.437, 3.522, -2.543, 1.616, 0.537	-3.8169, 2.182, -2.904, -3.278, -0.055, 0.132, -0.246, 0.146, -0.355, -0.250,	% Sigmoid Symmetric Transfer Function function a = transiq apply (n) $a = 2 ./ (1 + \exp(-2*n)) - 1;$	764.85	759.74
M ₂	Land Use and Land Cover, Depth of	0.295, 0.205, 0.2959, 0.2058	3.166, -2.991, 2.594, -3.490, -2.790, -0.029, -0.250, 0.732, 0.002, -0.265,		789.80	792.38
M ₃	Water table, Slope of ground, Drainage Density.	-0.8016, -1.4938, 2.4272, 3.4318, 4.4047,	3.166, -2.991, -2.594, -3.490, -2.790, 3.4130.149, -0.194 0.195, 0.135, -		787.46	769.31
M ₄		-3.817, 2.182, -2.904, -2.991, -2.790, -3.490,	0.199, 0.576, 0.172, -0.637, -0.010,		783.53	773.32

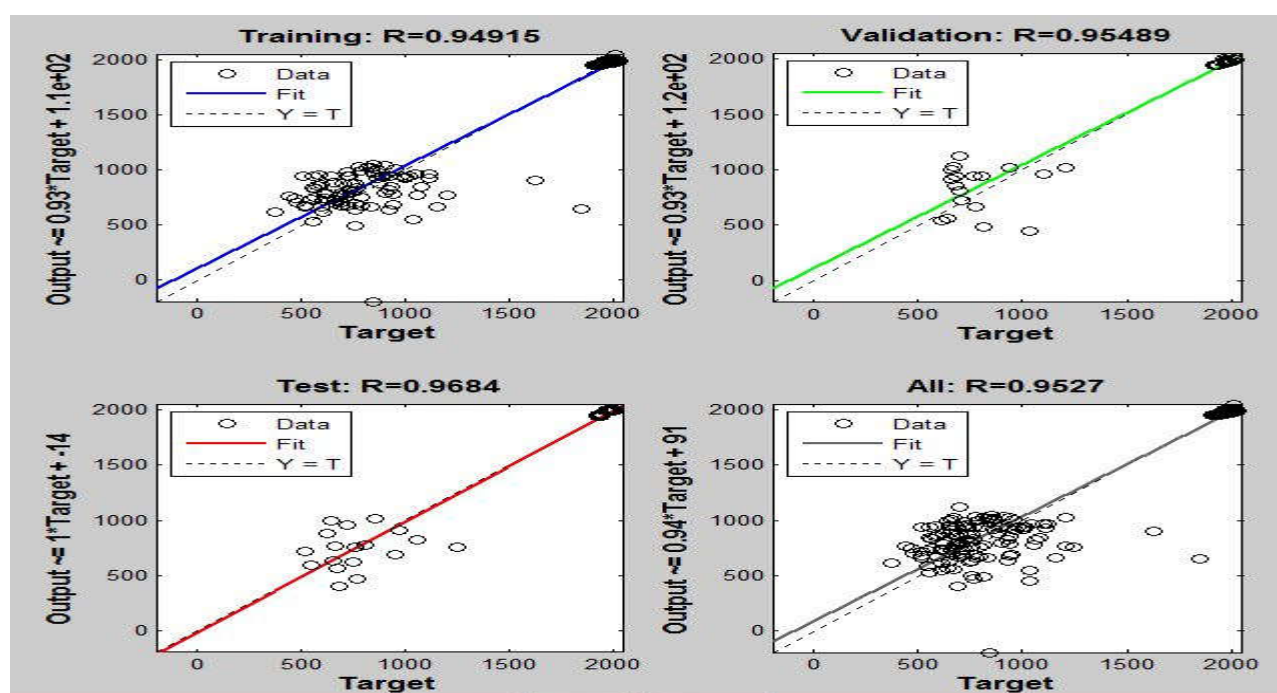
Table 3. the result containing the ANNs model for the district of Bankura.

Model	Input parameters	Multiple Regression Coefficients	Weights	Transfer Function
M ₁	Monthly Rainfall,	4.437, 3.522, -2.543, 1.616, 0.537	-3.8169, 2.182, -2.904, -3.278, -0.055, 0.132, -0.246, 0.146, -0.355, -0.250,	% Sigmoid Symmetric Transfer Function function a = transiq apply (n) $a = 2 ./ (1 + \exp(-2*n)) - 1;$
M ₂	Land Use and Land Cover, Depth of	0.295, 0.205, 0.2959, 0.2058	3.166, -2.991, 2.594, -3.490, -2.790, -0.029, -0.250, 0.732, 0.002, -0.265,	
M ₃	Water table, Slope of ground, Drainage	-0.8016, 1.4938, 2.4272, 3.4318, 4.4047,	3.166, -2.991, -2.594, -3.490, -2.790, 3.4130.149, -0.194 -0.195, 0.135,	
M ₄	Density.	-3.817, 2.182, -2.904, -2.991, -2.790, -3.490,	0.199, 0.576, 0.172, -0.637, -0.010,	

Table 4. Result of Artificial Neural Networks (ANNs) Model for the district of Bankura.

Model no	Rainfall in mm	Runoff in mm		Correlation Coefficient 'R'	Nash-Sutcliffe Efficiency (NSE)	Mean Absolute Error (MAE)	Root Means Squared Error (RMSE)	Model Error in %	Remarks
		Observed	Predicted						
M ₁	1408.48	764.74	759.74	0.9527	82.38	36.78	45.49	-1.091	Model M ₃ is the best fitted model.
M ₂		789.80	792.38	0.9707	88.92	38.57	48.52	0.615	
M ₃		787.46	771.06	0.9728	97.49	35.47	42.00	0.060	
M ₄		783.53	773.32	0.9626	95.24	45.79	62.75	0.290	

The behaviour of the ANNs during training, testing, and validation are shown in figure 11. The correlation coefficient value 'r' above 97% indicates the strong positively correlated with each other (observed and predicted flow). The training process of the model network was stopped when the error of the data series was minimal. The objective of the training process is to reduce error based on model performance (NSE, RMSE, and MAE). The validation set is used to obtain the best result of the model network. The values of training "r" = 0.96972, testing 'r' = 0.97783, and validation 'r' = 0.98662, represents the good agreement with correlation coefficient values as shown in figure 11. The data pairs are very closer to the diagonal line represent the excellent prediction. For events model 'M₃' and 'M₄', the Nash-Sutcliffe Efficiency (NSE) greater than 95% (shown in table 2) indicates the excellent results.

**Figure 6. Multiple Linear Regression curve fitting of model M₁.**

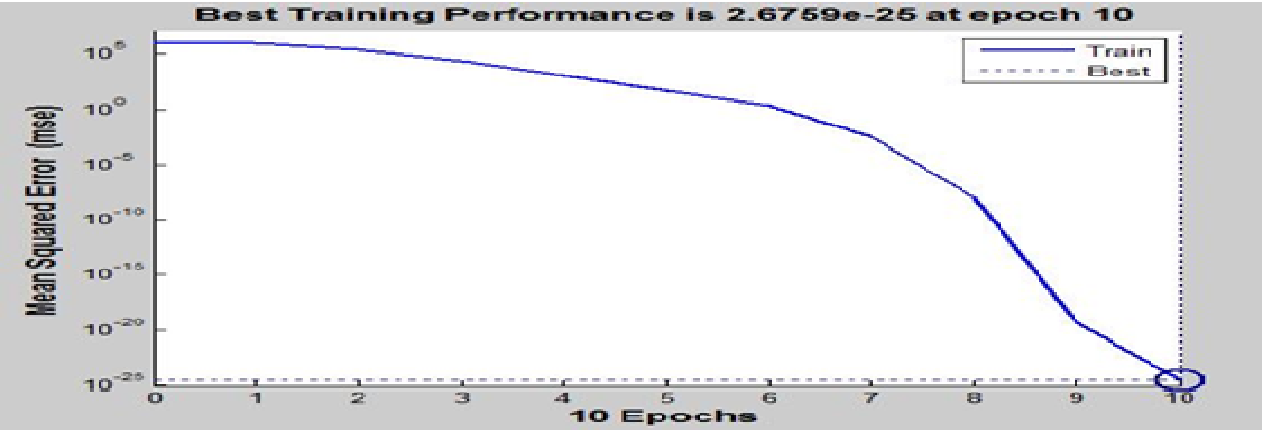


Figure 7. Training performance of model M₁

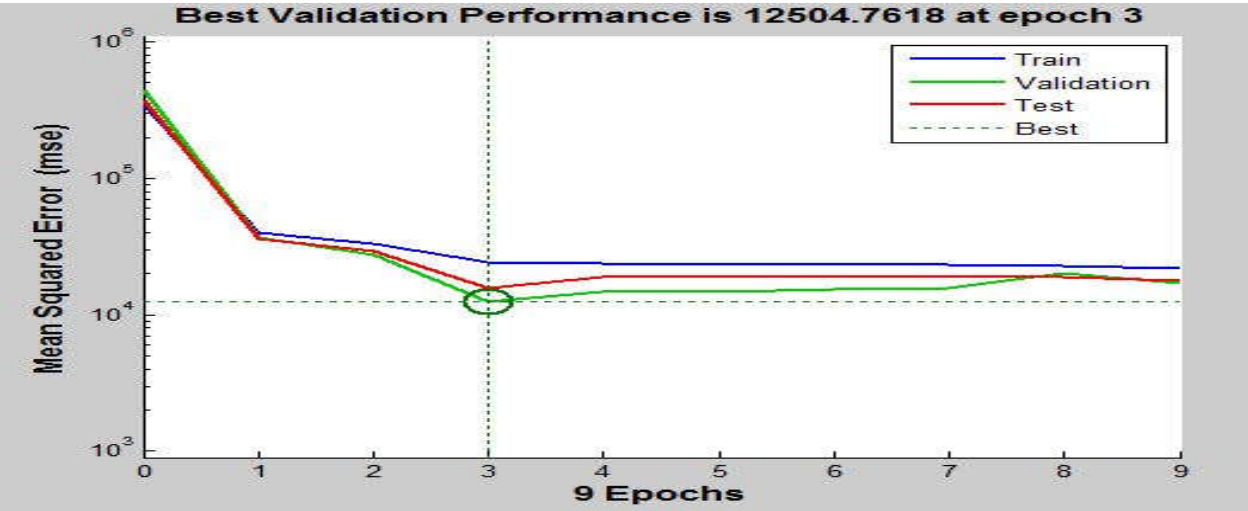


Figure 8. Validation performance of model M₂.

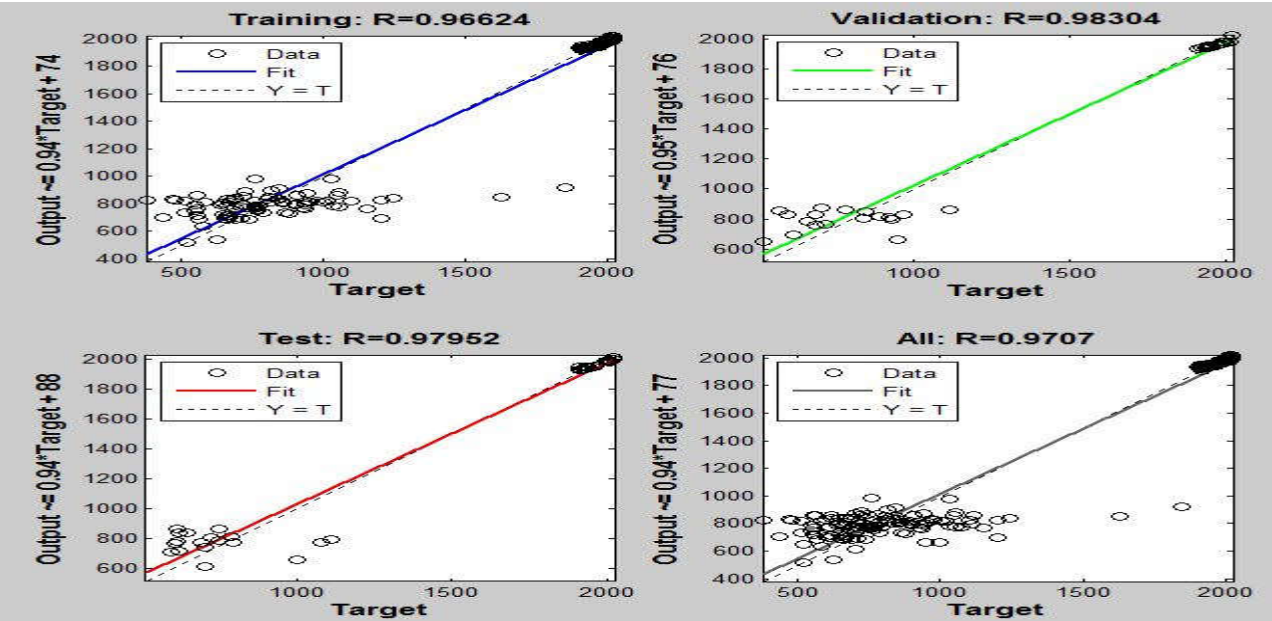


Figure 9. Multiple Linear Regression curve fitting of model M₂.

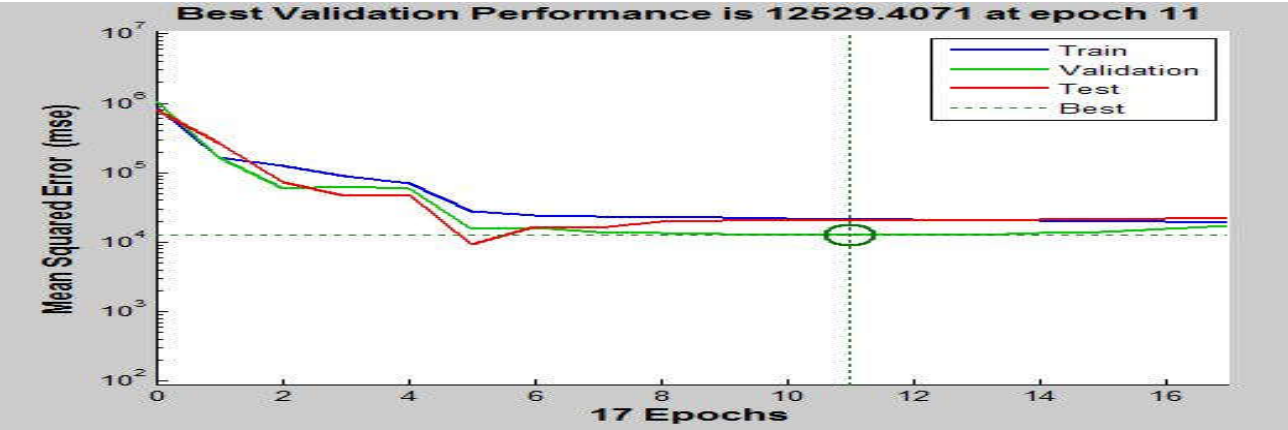


Figure 10. Validation performance of model M3.

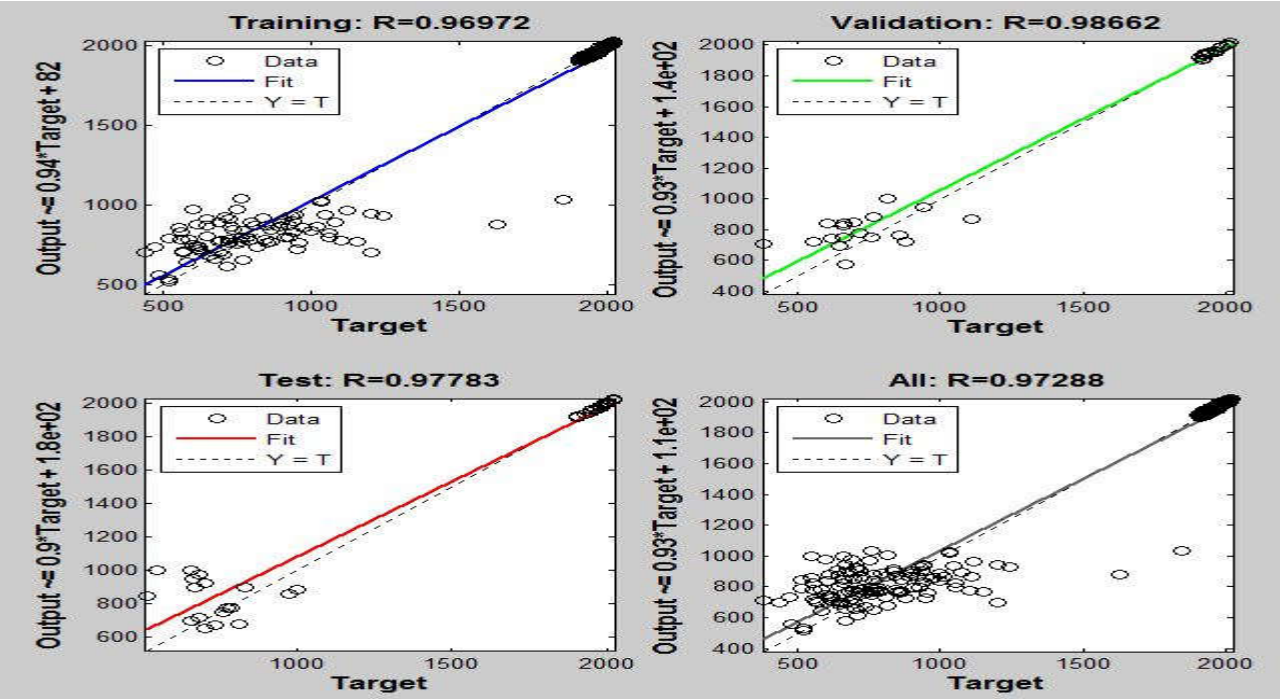


Figure 11. Validation performance of model M3.

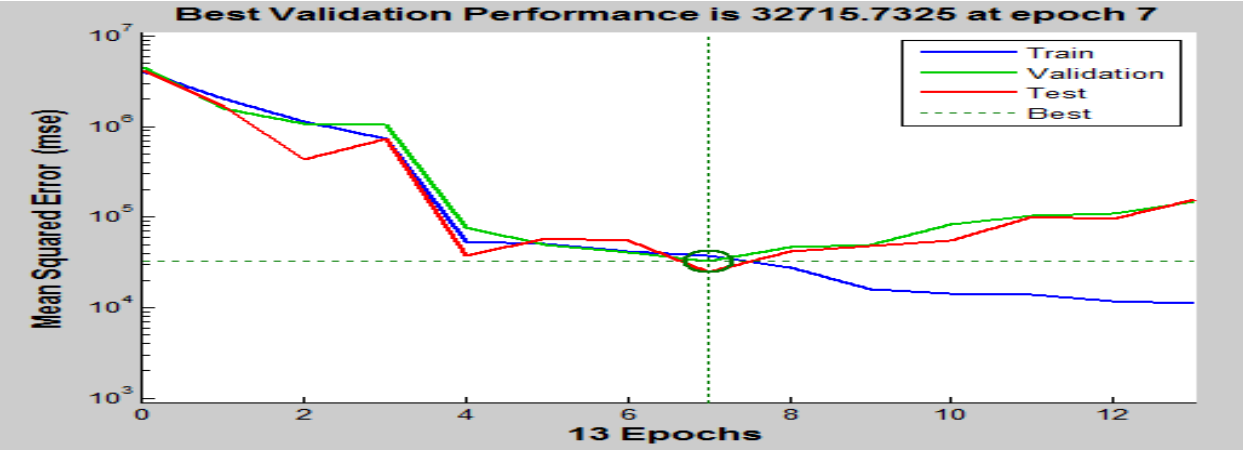


Figure 12. Validation performance of model M4.

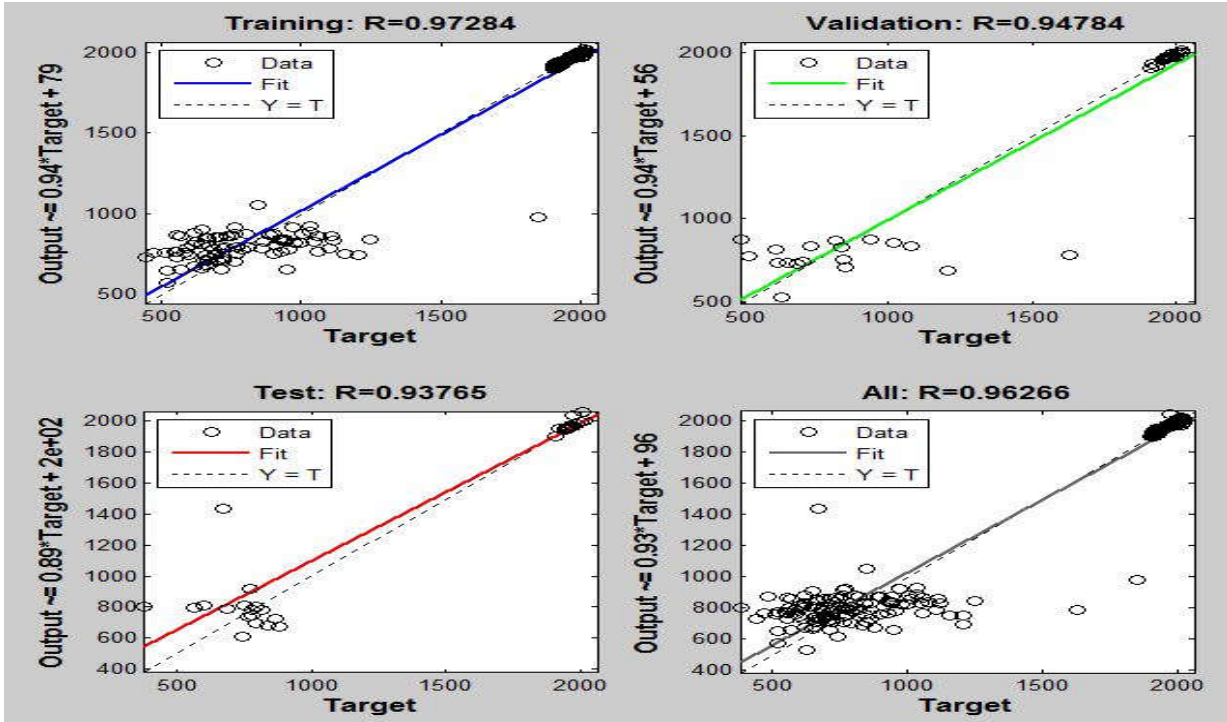


Figure 13. Multiple Linear Regression Curve Fitting of model M4.

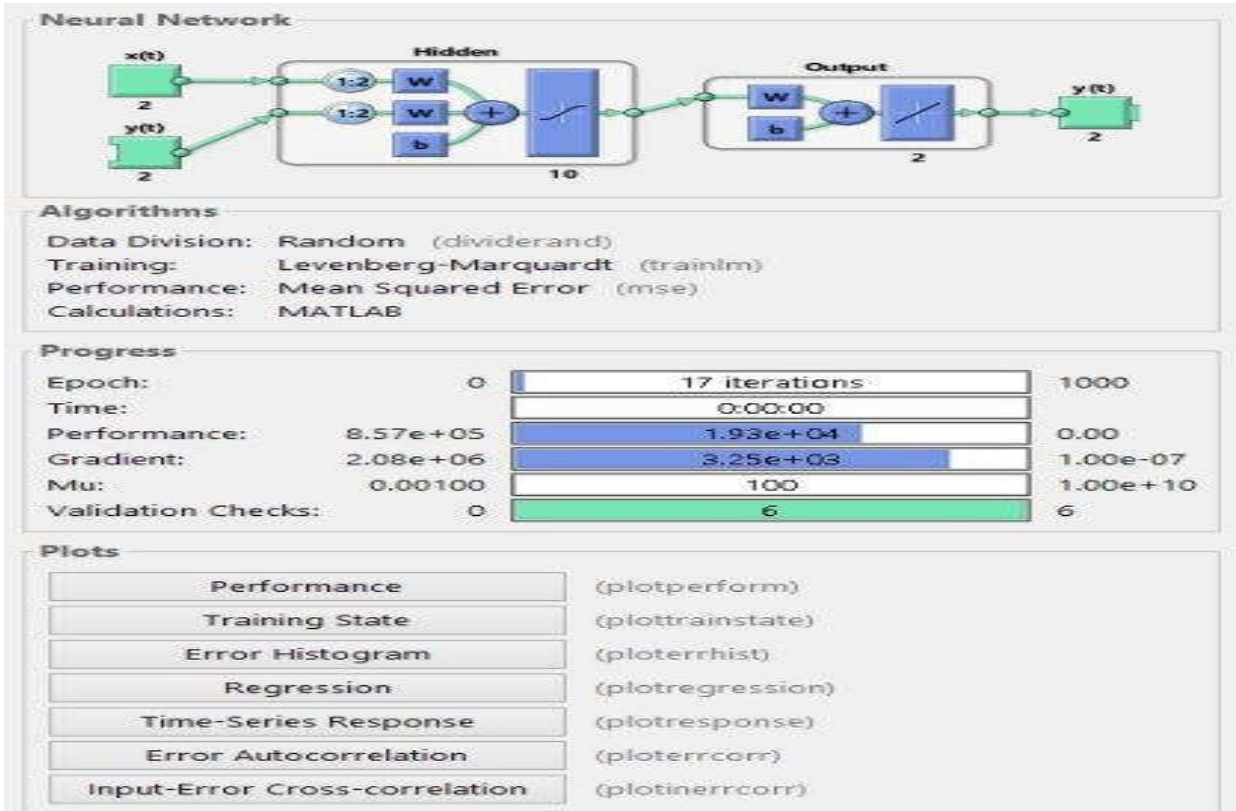


Figure 14. Details of Artificial Neural Network of model M3.

The predicted result is useful in the field of water resources management and planning for decision making [1,29,30]. Apart from that, the modelling can also useful for rural as well as an urban planners to take necessary measures.

6. Conclusions

The present study has performed for prediction of run-off in Lower Gangetic Basin with the help of ANNs model. The research has point out the following conclusions:

- (i) The prediction of run-off is closer to the observed data.
- (ii) Accuracy of the simulated result using ANNs is found above 97% , which indicates excellent prediction.
- (iii) During performance analysis of the models, less error found in 'M₃' model.
- (iv) In case of other event models, 'M₂' and 'M₃', the NSE was found greater than 97% , which shows better results.
- (v) NSE found greater than 95% for event model 'M₃' and 'M₄', indicates excellent predictions (results) for the district Bankura which is located on Lower Gangetic Basin.

The predicted result (model M₃) is useful in the field of management sustainable development for future. It is also found, the equation of Kothyari and Garde (1991) [16] is more suitable for Lower Gangetic Basin, district Bankura, West Bengal. Vegetal factor and catchment's slope are the important parameters to predict runoff of a river basin.

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