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Assessment of Runoff via Precipitation using Neural Networks: Watershed Modelling for Developing Environment in Arid Region

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ABSTRACT

This work describes the application of three different neural network, (i) Back propagation neural network (BPNN), (ii) Layer Recurrent Neural Network (LRNN) and (iii) Radial Basis Fewer Network (RBFN) model, to predict runoff. Here, two scenarios were considered for developing the models. Scenario 1 exclusive of evapotranspiration and Scenario 2 with evapotranspiration are considered for experiencing the impact on runoff. Performance indicators entailed Scenario 2 performed best as compared to Scenario 1. Two watersheds Loisingha, and Saintala were considered for study. In Loisingha watershed, LRNN performed best with architecture 4-3-1 following tangential sigmoid transfer function. At Saintala, both LRNN and BPNN performed in parallel with small deviation of prediction and LRNN performed best among three networks with model architecture 4-2-1 using Log-sig transfer function for predicting runoff.

Keywords: Evapotranspiration, neural network, precipitation, runoff, temperature, watershed

INTRODUCTION

Water availability is the computation of runoff resulting from precipitation and its abstracts on watershed. The correlation between precipitation and evapotranspiration involves mapping for measuring runoff. Inclusion of temperature in addition to the above inputs is helpful to measure the accuracy of model. In this context, the present study gives an idea for estimating runoff. Estimation of runoff is achieved using hydrological modelling to understand catchment behaviours, impacts of climate, and land use changes. Common methods for estimation include the physical, statistical, and combined approaches to analyze available data.

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Artificial Neural Network (ANN) was utilized for computing the model using daily stream flows over Leaf River Basin (Smith & Eli, 1995; Tokar & Johnson 1999). Ghose and Samantaray (2018a) used regression and BPNN technique for hydrological modelling at Suktel watershed. Lungu (1991) observed the non-linear relationship between monthly rainfall and runoff. Srinivasulu and Jain (2006) found the factors which affected the runoff response of a watershed. Chen and Adams (2006) found conceptual rainfall-runoff models that were broadly used in hydrological modelling. Ghose and Samantaray, (2018b) employed BPNN and RBNN techniques to evaluate water table instability in sparse rainfall province, Odisha. Zhao (1992) implemented Xinanjiang (XAJ) model for measuring rainfall-runoff in China. Kothyari and Singh (1999) utilised different methods for estimating monthly runoff during monsoon months from June to October, in Northwest Iran. RBFN showed similar modelling results to that of multilayer perceptron neural network (NN) in building relationship between rainfall-runoff (Dawson & Wilby, 2001; Kumar et al., 2005; Shamseldin et al., 2007; Zakermoshfegh et al., 2008). Growth of hybrid NNs with conceptual model has received substantial consideration (Lee et al., 2002; Jain & Srinivasulu, 2006). Ghose and Samantaray, (2018c) employed BPNN, RBFN and Non Linear Multilayer Regression techniques to develop sediment rating models for period of monsoon season for Mahanadi river basin upstream of Tikarapada. Kisi et al. (2013) compared the accuracy of Gene Expression Programming, Adaptive Neuro-Fuzzy Inference System and ANN techniques in modelling rainfall-runoff process in Turkey. Chandwani et al. (2015) presented applications in modelling rainfall-runoff relations which replaced time consuming conventional mathematical techniques. Asadi et al. (2013) proposed a model which was a hybrid of data pre-processing methods, genetic algorithms and Levenberg–Marquardt (LM) algorithm for learning feed forward neural networks. Javan et al. (2015) investigated impacts of climate change on runoff using ANN for various gauging station of Gharehsoo River Basin in the northwest of Iran. Shoaib et al. (2014) employed hybrid Multilayer Perceptron Neural Network (MLPNN) and the Radial Basis Function Neural Network (RBFNN) to predict rainfall-runoff modelling at Brosna catchment. Descent neural network was considered to predict sediment load at Salabheta gauging station, India (Samantaray & Ghose, 2018). The objective is to develop correlation of rainfall-runoff and prediction of runoff through various neural networks considering precipitation, maximum and minimum temperature as input. Also addition of evapotranspiration with scenario one is employed to establish rainfall runoff co-relation.

STUDY AREA AND DATA COLLECTION

Two watersheds of Bolangir, Odisha, India, were taken into consideration for the proposed study area. The watersheds are located at Loisingha and Saintala having geographical area 317.6 Sq km, and 454.43 Sq km as shown in Figure 1. The purpose of this study was to predict runoff in two watersheds to assess the drainage capacity of watershed during monsoon period ranging from 1998 to 2017. The two watersheds are situated in the upstream of Hirakund reservoir. The geo coordinate of the watersheds are latitude 21º88′ 36″ N and longitude 84º 90′ 75″ E.

The average monthly precipitation, highest monthly average temperature and least monthly average temperature and evapotranspiration data for month of monsoon (May to October) from the period 1998-2017 spanning over 20 years were collected from India Meteorological Department (IMD) Bhubaneswar. The monthly runoff data were collected from soil conservation office, Bolangir. Average rainfall is within the range of 130cm to 141cm. Since the study area is within less rainfall region, prediction of runoff is necessary.

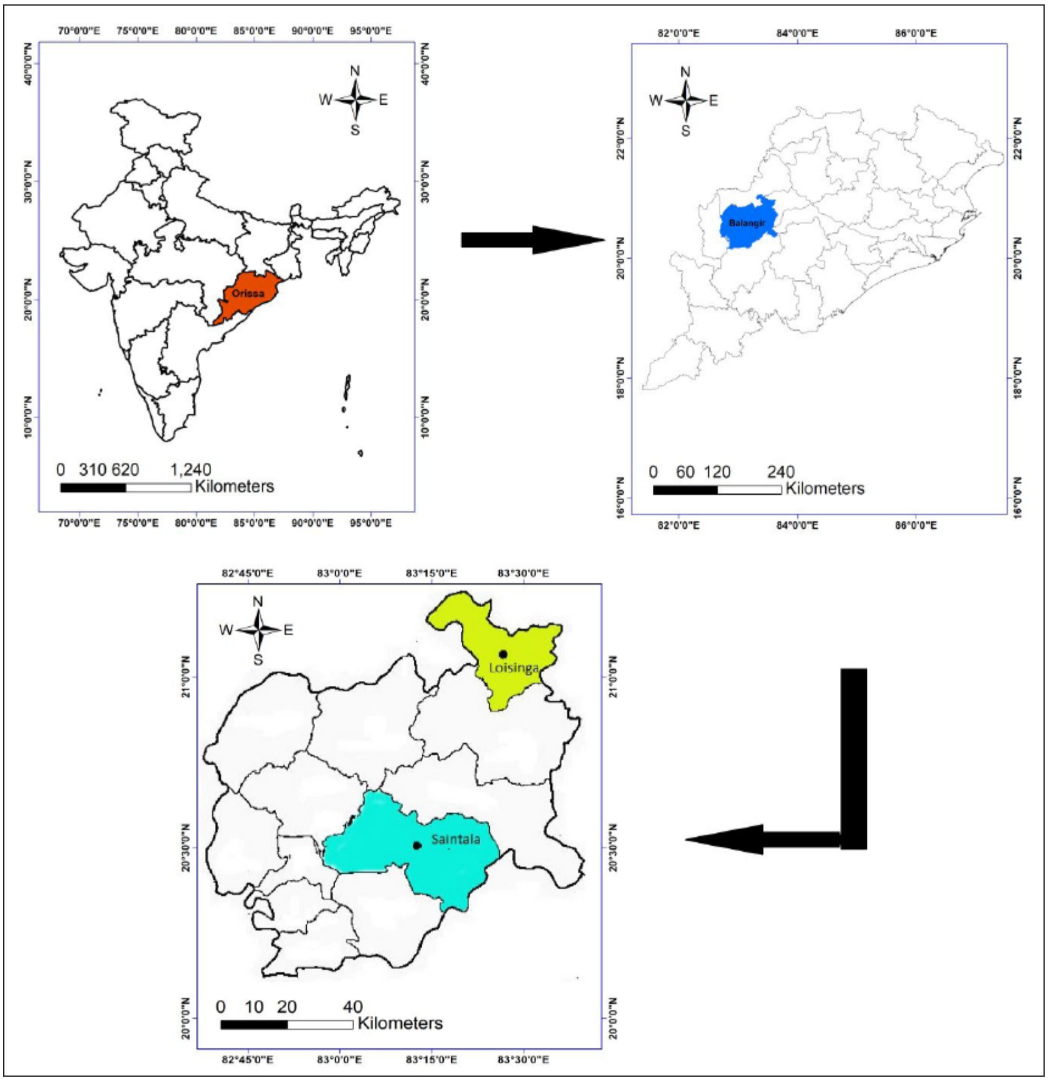


Figure 1. Study area

MATERIAL AND METHOD

Back-propagation Neural Network

The multi-layer perceptron network with supervised learning model which minimizes the error using weight adoption by applying back propagation of error is identified as BPNN. Back propagation was used to compute the gradient of the error of the network with respect to adjustable weights of the network. Further, this gradient used a modest stochastic gradient descent algorithm to determine weights that could reduce the error. Back propagation permits quick convergence on acceptable local minima for error in the kind of networks to which it is suited. It is significant to point that back propagation networks are essentially multiple layers (with single input, single hidden and single output layer). For the hidden layer to serve any suitable function, multiple layer networks should have non-linear activation functions to trigger the multiple layers. Back propagation neural network is a three-layered feed forward architecture, which accelerates input layer, hidden layer and output layer for functioning of back propagation activities in three stages, i.e. learning or training, testing or inferences and validation. Figure 2 shows the l-m-n (l input neurons, m hidden neurons, and n output neurons) architecture of a back propagation neural network model.

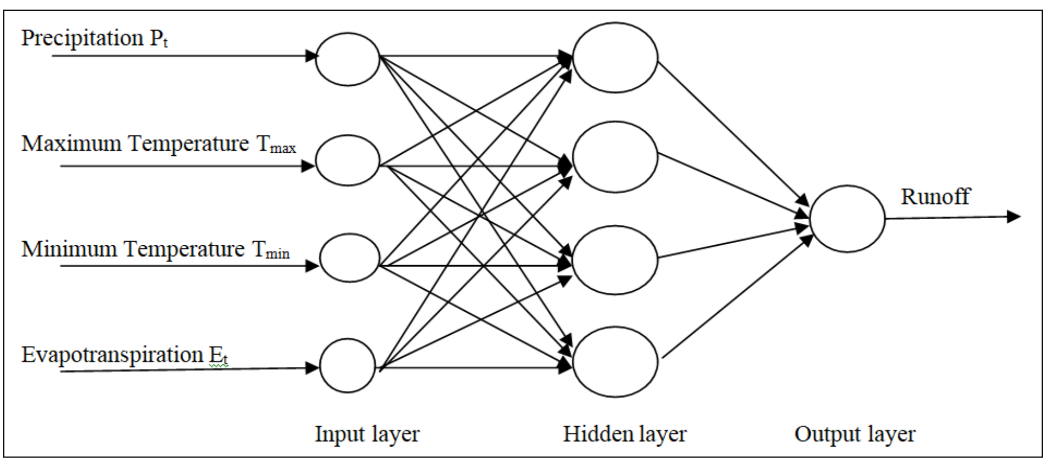


Figure 2. BPNN model with 4 input

Radial Basis Function Network

Basically RBFN comprises a huge number of simple and highly interconnected artificial neurons and can be organized into numerous layers, i.e. input layer, hidden layer, and output layer as presented in Figure 3.

Algorithm of RBFN (Fahrmeir et al., 2013). Following steps shows the basic algorithm of RBFN.

Input layer:

Inputs of normalized data is to be processed connecting with direct transfer function and pattern of interaction is to be directed through weights of neurons. Number of nodes in the input layer is equal to the number of input parameter.

Hidden layer:

The hidden layer helps in processing patterns merged through input and weights interlinked through input-output. Radial symmetry functions are used as transfer functions for processing the net. The output of unit i_m unit $V_i(x_i)$ in the hidden layer

$$V_i x_i = e^{-\frac{x^2}{\sigma^2}} \tag{1}$$

Where $x^2 = (x_{ji} - \widehat{x_{ji}})^2 \; x_{ji}$

In which x_{ji} is the centre of RBF unit for input variables

σ is the width of RBF unit

$\widehat{x_{ji}}$ average of input variables

Output layer:

In this layer the output of the neural network is evaluated. The output of the neuron network is evaluated as

$$y_{net} = \sum_{i=1}^{H} w_{im} v_i(x_i) + w_0 \quad y_{net} \; w_{im} \; w_0 \tag{2}$$

Where H = number of hidden node

y_{net} = output value of m_{th} node in output layer for the n_{th} incoming pattern

w_{im} = weight between i_{th} RBF unit and m_{th} output node

w_0 = biasing term at n_{th} output node

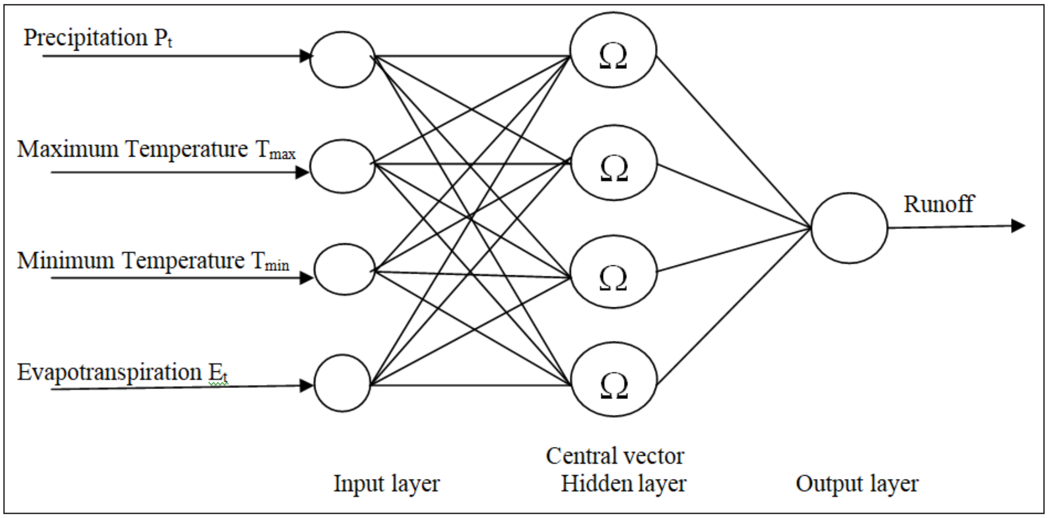


Figure 3. Architecture of RBFN.

Layer Recurrent Neural Network

LRNN is developed through an Elman network which is a three-layer network with the addition of context units. The hidden layer is connected through context units merged with fixed unit weight. The fixed back-connections memorize copy of the ancestor of the hidden units for further processing. The network is allowing sequence prediction with multilayer perceptron networks.

Elman network is defined as

$$H_t = \sigma_h(W_h X_t + U_h H_{t-1} + b_h) \quad (3)$$

$$Y_t = \sigma_y(W_y H_t + b_y) \quad (4)$$

Where x_t = input unit
H_t = Hidden unit
Y_t = output unit
W, U, b= parameter matrices
σ_y, σ_h = Activation function

Each input unit is linked to every one hidden unit, in combination with context unit shown in Figure 4. The recurring connections permit the hidden units to recycle the information over multiple time steps, thus letting to determine temporal information that is confined in the sequential input and relevant to the target function.

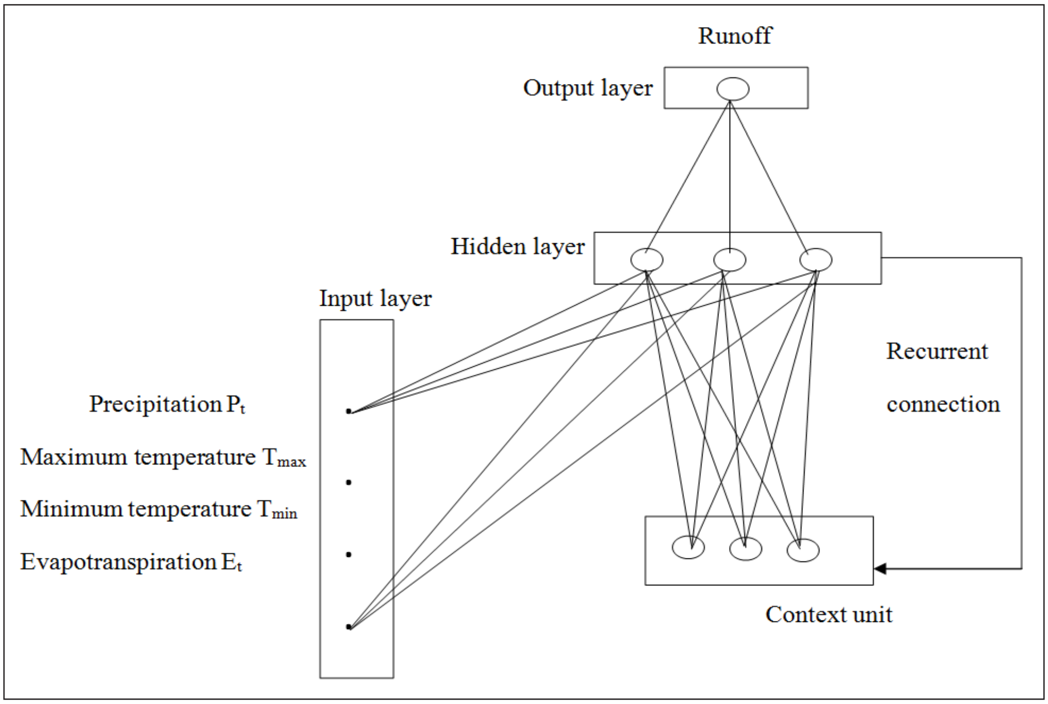


Figure 4. Architecture of LRNN

Processing and Preparation of Data

The monthly rainfall, highest monthly temperature, least monthly temperature were collected from IMD, Bhubaneswar and daily runoff data were collected from soil conservation office, Bolangir, Odisha, India for period of the monsoon months (May to October), from 1998-2017. The data collected from 1998-2011 (70% of data set) were used for training and from 2012-2017 (30%) were used for testing the network. Daily data were converted into monthly data, which finally helped in training and testing the model. The input and output data were scaled in such a way that every data fell within a quantified range before training. This process is known as normalization so that the normalized values are confined within the range of 0 to 1. The normalization equation which is used for scaling the data is

$$X_t = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (5)$$

Where X_t = transformed data series, X = original input data series, X_{min} = minimum of original input data series, X_{max} = maximum of original input data series.

Evaluating Criteria

Coefficient of determination, mean square error (MSE) and root mean square error (RMSE) are the evaluating standards to determine the best model. To select the perfect model for this area of study, the condition is MSE, RMSE must be minimum and coefficient of determination must be maximum.

Co-efficient of determination:

$$(\mathrm{R}^2) = 1 - \frac{(\sum_{\mathrm{i=1}}^{\mathrm{N}} x_{comp}^{i} - \bar{x}_{comp})^2}{(\sum_{\mathrm{i=1}}^{\mathrm{N}} x_{obs}^{i} - \bar{x}_{obs})^2} \quad (6)$$

The coefficient of determination value specifies the percent of variation in one variable explained by the other variable.

$$\text{MSE} = \frac{1}{n}\sum_{j=1}^{n}(x_{comp}^{i} - x_{obs}^{i})^2 \quad (7)$$

$$\text{RMSE} = \frac{\sum_{i=1}^{N}(x_{comp}^{i} - \bar{x}_{comp})(x_{obs}^{i} - \bar{x}_{obs})}{\sqrt{\sum_{i=1}^{N}(x_{comp}^{i} - \bar{x}_{comp})^2}(x_{obs}^{i} - \bar{x}_{obs})^2} \quad (8)$$

Where i= dummy variable

N= Number of data

x_{comp}^{i} = Predicted data

x_{obs}^{i} = Observed data

$\bar{x}_{comp}$ =Mean predicted data

$\bar{x}_{obs}$ = Mean observed data

RMSE is the root of mean squared error. RMSE also has non negative values and close to zero gives the best performance.

RESULTS AND DISCUSSIONS

Analysis of Results with Scenario 1 and Scenario 2

Scenario 1 was estimated by considering precipitation, maximum temperature, and minimum temperature as input for predicting runoff in two watersheds. The basic equation used for predicting the runoff in two watersheds basing upon the equation $Q_{t} = f(P_{t}, T_{max}, T_{min},)$ for Scenario1. Similarly Scenario 2 was estimated by considering precipitation, maximum temperature, minimum temperature, and evapotranspiration as input for predicting runoff in two watersheds. Equation used for predicting the runoff in two watersheds basing upon the equation $Q_{t}= f(P_{t}, T_{max}, T_{min}, E_{t})$ for scenario 2.

Results for Scenario 1 at Loisingha. Scenario 1 was estimated by considering precipitation, maximum temperature, and minimum temperature as input for predicting runoff at Loisingha watershed. The results are presented in Table 1, Table 2, and Table 3.

Table 1
Results of BPNN for Scenario 1

Scenario 1	Transfer Function	Architec-ture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
$P_{t,}$, T_{max}, T_{min}	Tansig	**3-2-1**	**0.00883**	**0.03367**	**0.09396**	**0.18351**	**0.8691**	**0.8376**
		3-3-1	0.00608	0.00459	0.07823	0.06776	0.7809	0.7289
		3-4-1	0.00939	0.07341	0.09691	0.27093	0.7733	0.7194
		3-5-1	0.00724	0.64751	0.08509	0.80464	0.8004	0.7475
		3-9-1	0.00115	0.00324	0.03394	0.05726	0.7768	0.7067
	Logsig	3-2-1	0.00963	0.00865	0.02151	0.03432	0.8472	0.7989
		3-3-1	0.00719	0.00686	0.03453	0.06392	0.8591	0.8112
		3-4-1	0.00082	0.00893	0.02059	0.03595	0.8324	0.7817
		3-5-1	**0.00078**	**0.00727**	**0.02429**	**0.06358**	**0.8713**	**0.8215**
		3-9-1	0.00818	0.00637	0.03435	0.06131	0.8781	0.8165
	Purelin	3-2-1	0.00856	0.00367	0.02925	0.05802	0.8553	0.8015
		3-3-1	0.00991	0.00471	0.03148	0.06380	0.7961	0.7511
		3-4-1	0.00975	0.00179	0.03122	0.04448	0.8431	0.7927
		3-5-1	0.00972	0.00378	0.03117	0.06138	07928	0.7521
		3-9-1	**0.00198**	**0.00512**	**0.03461**	**0.07079**	**0.8693**	**0.8177**

Table 2
Results of LRNN network for Scenario 1

Scenario 1	Transfer Function	Archi-tecture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
P_t, T_{max}, T_{min}	Tansig	**3-2-1**	**0.00105**	**0.00206**	**0.03170**	**0.04538**	**0.9215**	**0.8889**
		3-3-1	0.00551	0.01735	0.07711	0.13171	0.9004	0.8672
		3-4-1	0.00963	0.03709	0.09813	0.19253	0.8841	0.8521
		3-5-1	0.00102	0.03021	0.03165	0.17381	0.8933	0.8662
		3-9-1	0.00187	0.00514	0.03587	0.07080	0.9137	0.8748
	Logsig	3-2-1	0.00653	0.00516	0.01151	0.00242	0.8772	0.8289
		3-3-1	0.00419	0.00386	0.02453	0.01392	0.8891	0.8412
		3-4-1	0.00062	0.00593	0.02059	0.01095	0.8624	0.8117
		3-5-1	0.00048	0.00427	0.01429	0.00348	0.8913	0.8515
		3-9-1	**0.00418**	**0.00337**	**0.01435**	**0.00131**	**0.9081**	**0.8665**
	Purelin	3-2-1	0.00549	0.00427	0.02458	0.05802	0.8295	0.7831
		3-3-1	0.00693	0.00491	0.02964	0.05721	0.8463	0.8174
		3-4-1	0.00629	0.00582	0.02991	0.04082	0.8417	0.8106
		3-5-1	**0.00294**	**0.00184**	**0.03092**	**0.05739**	**0.8735**	**0.8291**
		3-9-1	0.00458	0.00354	0.03071	0.06392	0.8432	0.8051

Table 3
Results of RBFN network for Scenario 1

Scenario 1	Architecture	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
P_t, T_{max}, T_{min}	4-0.2-1	0.00429	0.00628	0.00432	0.00418	0.8014	0.7528
	4-0.3-1	0.00372	0.08125	0.00201	0.02016	0.8273	0.7938
	4-0.5-1	0.00512	0.05934	0.02639	0.08429	0.8195	0.7682
	4-0.7-1	0.00384	0.01937	0.02732	0.06418	0.8216	0.7828
	4-0.9-1	**0.00502**	**0.00923**	**0.02013**	**0.04962**	**0.8526**	**0.8093**

Results for Scenario 2 at Loisingha. Here to evaluate the model efficiency of various architectures, different transfer functions like tangential sigmoidal, logarithmic sigmoidal and purelin were used to establish the model performance. Every architecture criteria for evaluation is mean square error training, testing, root mean square error training, testing and coefficient of determination. In Table 4 for Tan-sig function in BPNN, 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Tan-sig function the best model architecture was found to be 4-9-1 which possesses MSE training value 0.00679, MSE testing value 0.00376, RMSE training value 0.02645 RMSE testing value 0.05404 and coefficient of determination for training 0.9587 and testing 0.9287. For Log-sig 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Log-sig function the best model architecture was found to be 4-2-1 which possess MSE training value 0.00463 MSE testing value 0.00165, RMSE training value 0.01591 RMSE testing value 0.03432 and coefficient of determination value training 0.9662, testing value 0.9327. For Purelin 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Purelin function the best model architecture was found to be 4-4-1 which possess MSE training value 0.00851 MSE testing value 0.00325, RMSE training value 0.02978, RMSE testing value 0.05374 and coefficient of determination value training 0.9592 and testing value 0.9218. The detailed results are presented in Table 4.

Table 4
Results of BPNN at Loisingha for Scenario 2

Scenario 2	Transfer Function	Architecture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
P_t, T_{max}, T_{min}, E_t	Tansig	4-2-1	0.00806	0.00417	0.02839	0.06163	0.9412	0.9153
		4-3-1	0.00795	0.00575	0.02815	0.07584	0.9355	0.9073
		4-4-1	0.00472	0.00256	0.09175	0.05493	0.9075	0.8807
		4-5-1	0.00471	0.00761	0.02805	0.01732	0.9289	0.8991
		4-9-1	**0.00679**	**0.00376**	**0.02645**	**0.05404**	**0.9587**	**0.9287**
	Logsig	**4-2-1**	**0.00463**	**0.00165**	**0.01591**	**0.03432**	**0.9662**	**0.9327**
		4-3-1	0.00193	0.00486	0.03453	0.06342	0.9186	0.8812
		4-4-1	0.00424	0.00193	0.02559	0.03585	0.9424	0.9017
		4-5-1	0.00589	0.00427	0.02469	0.06358	0.9213	0.8915
		4-9-1	0.00818	0.00337	0.03465	0.06131	0.9481	0.9165
	Purelin	4-2-1	0.00397	0.00369	0.03373	0.05172	0.9147	0.8823
		4-3-1	0.00858	0.00342	0.02297	0.05495	0.9254	0.8937
		4-4-1	**0.00851**	**0.00325**	**0.02978**	**0.05374**	**0.9592**	**0.9218**
		4-5-1	0.00843	0.00345	0.02935	0.05856	0.9347	0.9028
		4-9-1	0.00852	0.00397	0.02954	0.05652	0.9443	0.9115

Similarly the LRNN results are discussed below for Loisingha station. For Tan-sig 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance revealed in Table 5. For Tan-sig function the best model architecture was found to be 4-3-1 which possessed MSE training value 0.00748, MSE testing value 0.00336, RMSE training value 0.02734, RMSE testing value 0.05796 and coefficient of determination value training 0.9972, testing value 0.9621. For Log-sig 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Log-sig function the best model architecture was found to be 4-2-1 which possessed MSE training value 0.00133, MSE testing value 0.00285, RMSE training value 0.03511, RMSE testing value 0.05296 and coefficient of determination value training 0.9783 testing value 0.9588. For Purelin 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Purelin function the best model architecture was found to be 4-4-1 which possessed MSE training 0.00975, MSE testing 0.00179, RMSE training 0.03122, RMSE testing 0.04448, and coefficient of determination training 0.9831, testing 0.9579.

Table 5
Results of LRNN at Loisingha for Scenario 2

Scenario 2	Transfer Function	Architecture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
$P_{t,}$, T_{max},, $T_{min,}$ E_t	Tansig	4-2-1	0.00986	0.00125	0.13887	0.03598	0.9583	0.9267
		4-3-1	**0.00748**	**0.00336**	**0.02734**	**0.05796**	**0.9972**	**0.9621**
		4-4-1	0.00451	0.00371	0.02123	0.05891	0.9825	0.9566
		4-5-1	0.00489	0.00112	0.02211	0.03181	0.9813	0.9508
		4-9-1	0.00391	0.00955	0.01977	0.03090	0.9732	0.9495
	Logsig	**4-2-1**	**0.00133**	**0.00285**	**0.03511**	**0.05296**	**0.9783**	**0.9588**
		4-3-1	0.00937	0.00497	0.03061	0.07054	0.9375	0.9107
		4-4-1	0.00124	0.00654	0.03217	0.07908	0.9313	0.9002
		4-5-1	0.00513	0.00252	0.12459	0.05019	0.9724	0.9533
		4-9-1	0.00134	0.00653	0.03786	0.08080	0.9376	0.9016
	Purelin	4-2-1	0.00856	0.00367	0.02925	0.05802	0.9723	0.9415
		4-3-1	0.00991	0.00471	0.03148	0.06380	0.9601	0.9394
		4-4-1	**0.00975**	**0.00179**	**0.03122**	**0.04448**	**0.9831**	**0.9579**
		4-5-1	0.00972	0.00368	0.03117	0.06138	0.9528	0.9321
		4-9-1	0.00198	0.00512	0.03461	0.07079	0.9493	0.9277

Similarly Results of RBFN are presented in Table 6 in scenario various spread values were taken for simulation. Here spread values were considered within range of 0 to 1 i.e. preferably 0.2, 0.3, 0.5, 0.7 and 0.9 for predicating runoff from the considerable input parameters for mapping output. It was found that with a spread value 0.9 the RBFN showed best performance with architecture having 4-0.9-1 which possessed MSE training 0.00537 testing 0.00314, RMSE training 0.02317 testing 0.05589 and coefficient of determination training 0.9301 testing 0.9118

Table 6
Results of RBFN at Loisingha for Scenario 2

Scenario 2	Architecture	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
$P_{t,}$, T_{max},, $T_{min,}$ E_t	4-0.2-1	0.00582	0.00284	0.02816	0.02817	0.7826	0.7418
	4-0.3-1	0.00635	0.01175	0.02519	0.10851	0.7982	0.7799
	4-0.5-1	0.00822	0.00853	0.02867	0.09248	0.8448	0.7861
	4-0.7-1	0.00594	0.00497	0.02437	0.07049	0.9291	0.8827
	4-0.9-1	**0.00537**	**0.00314**	**0.02317**	**0.05589**	**0.9301**	**0.9118**

Results for Scenario 2 at Saintala using BPNN, LRNN and RBFN

For Tan-sig function in BPNN, 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Log-sig function the best model architecture was found to be 4-2-1 which possessed MSE training value 0.00278, MSE testing value 0.00894, RMSE training value 0.05174 RMSE testing value 0.09270 and coefficient of determination for training 0.9607 and testing 0.9383. For Tan-sig and Purelin 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. The detailed results are presented below in Table 7.

Table 7
Results of BPNN at Saintala for Scenario 2

Scenario 2	Transfer Function	Architecture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
P_t, T_{max}, T_{min}, E_t	Tansig	4-2-1	0.00283	0.00521	0.05461	0.04257	0.9491	0.9085
		4-3-1	0.00357	0.00217	0.05938	0.05283	0.9517	0.9133
		4-4-1	**0.00217**	**0.00171**	**0.04708**	**0.06458**	**0.9598**	**0.9208**
		4-5-1	0.00272	0.00901	0.05217	0.04347	0.9501	0.9116
		4-9-1	0.00267	0.00837	0.05154	0.04286	0.9499	0.9083
	Logsig	**4-2-1**	**0.00278**	**0.00894**	**0.05174**	**0.09270**	**0.9607**	**0.9383**
		4-3-1	0.00242	0.00116	0.04931	0.00136	0.9383	0.9185
		4-4-1	0.00309	0.00319	0.05566	0.05584	0.9505	0.9327
		4-5-1	0.00283	0.00655	0.05322	0.02559	0.9424	0.9234
		4-9-1	0.00269	0.00779	0.05107	0.02791	0.9358	0.9043
	Purelin	4-2-1	0.00297	0.00954	0.05932	0.03088	0.9537	0.9244
		4-3-1	0.00262	0.00347	0.05120	0.02167	0.9351	0.9026
		4-4-1	0.00269	0.00789	0.05117	0.02808	0.9273	0.8929
		4-5-1	**0.00283**	**0.01521**	**0.05461**	**0.02537**	**0.9595**	**0.9302**
		4-9-1	0.00357	0.02217	0.05938	0.01483	0.9317	0.8933

The LRNN results are discussed below for Saintala station. For Tan-sig, Log-sig, Purelin 4-2-1, 4-3-1, 4-4-1, 4-5-1, 4-9-1 architectures were taken into consideration for computation of performance. For Log-sig function the best model architecture was found to be 4-2-1 which possessed MSE training value 0.00632, MSE testing value 0.00612, RMSE training value 0.05130, RMSE testing value 0.07823 and coefficient of determination value training 0.9901, testing value 0.9827. Detailed results for other transfer functions are tabulated below in Table 8.

Similarly results of RBFN are presented in Table 9 with various spread values are taken for simulation. Here spread values were considered within range of 0 to1 i.e. preferably 0.2, 0.3, 0.5, 0.7 and 0.9 for predicating runoff from the considerable input parameters for mapping output. It was found that with a spread value 0.3 the RBFN showed best

Table 8
Results of LRNN at Saintala for Scenario 2

Scenario 2	Transfer Function	Archi-tecture	MSE		RMSE		R^2	
			Training	Testing	Training	Testing	Training	Testing
$P_{t,}$ T_{max},, $T_{min,}$ E_t	Tansig	4-2-1	0.00387	0.00173	0.06153	0.36293	0.9372	0.9085
		4-3-1	**0.00277**	**0.00529**	**0.05202**	**0.07634**	**0.9889**	**0.9772**
		4-4-1	0.00283	0.00998	0.05322	0.03159	0.9623	0.9454
		4-5-1	0.00293	0.00678	0.05406	0.09315	0.9797	0.9643
		4-9-1	0.00348	0.00341	0.05520	0.05950	0.9605	0.9528
	Logsig	**4-2-1**	**0.00632**	**0.00612**	**0.05130**	**0.07823**	**0.9901**	**0.9827**
		4-3-1	0.00313	0.00458	0.05594	0.06370	0.9647	0.9424
		4-4-1	0.00285	0.00879	0.05338	0.08293	0.9445	0.9385
		4-5-1	0.00418	0.01553	0.05846	0.10272	0.9734	0.9647
		4-9-1	0.00289	0.00567	0.05374	0.02381	0.9681	0.9523
	Purelin	**4-2-1**	**0.00238**	**0.00572**	**0.05136**	**0.02391**	**0.9893**	**0.9798**
		4-3-1	0.00312	0.00676	0.05587	0.02654	0.9577	0.9423
		4-4-1	0.00357	0.00541	0.05529	0.02325	0.9722	0.9622
		4-5-1	0.00182	0.00829	0.0426	0.02879	0.9636	0.9507
		4-9-1	0.00387	0.00173	0.06153	0.06293	0.9692	0.9585

performance with architecture having 4-0.3-1 which possessed MSE training 0.00214 testing 0.04255, RMSE training 0.05304 testing 0.03775 and coefficient of determination training 0.9429 testing 0.9125.

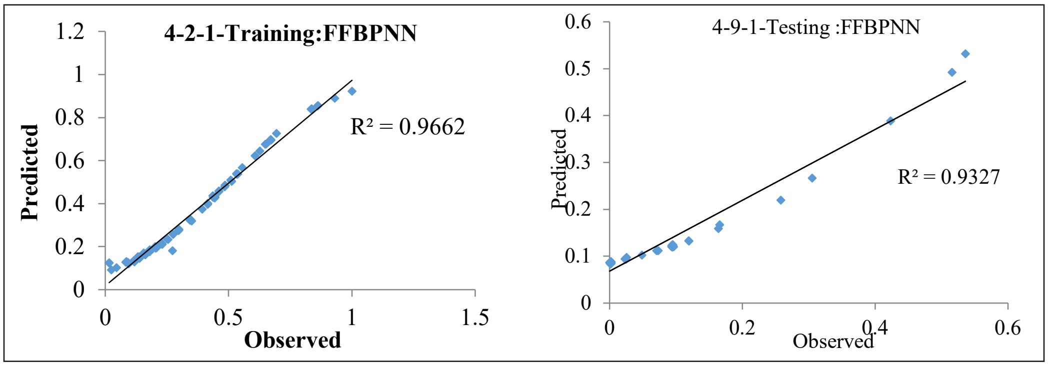
Table 9
Results of RBFN at Saintala for Scenario 2

Scenario 2	Architecture	MSE		RMSE		R^2	
		Training	Testing	Training	Testing	Training	Testing
$P_{t,}$ T_{max},, $T_{min,}$ E_t	4-0.2-1	0.04382	0.03821	0.04184	0.02339	0.9218	0.9063
	4-0.3-1	**0.00214**	**0.04255**	**0.05304**	**0.03775**	**0.9429**	**0.9125**
	4-0.5-1	0.00308	0.06891	0.05751	0.02567	0.9184	0.8953
	4-0.7-1	0.00343	0.04978	0.05867	0.02231	0.9027	0.8861
	4-0.9-1	0.00329	0.07897	0.06024	0.02454	0.8995	0.8606

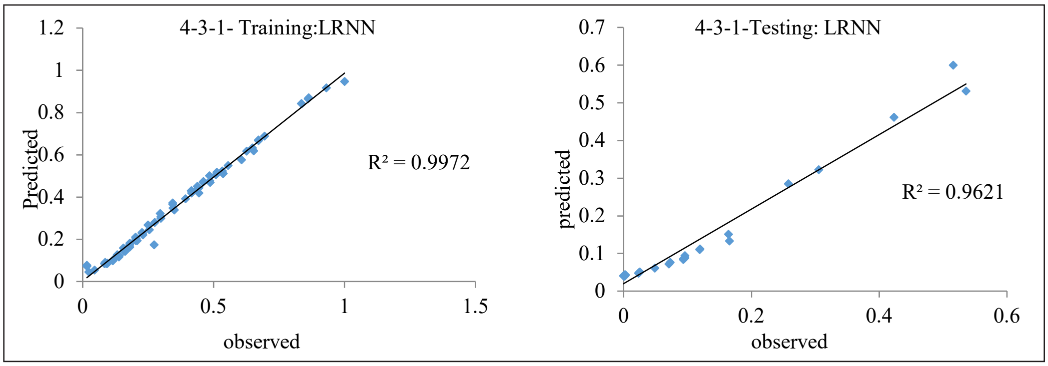
From the above research we found that among two scenarios while evapotranspiration was added with rainfall, maximum and minimum temperature all rainfall-runoff correlation models performs best as compared to prediction without considering evapotranspiration.

Simulation

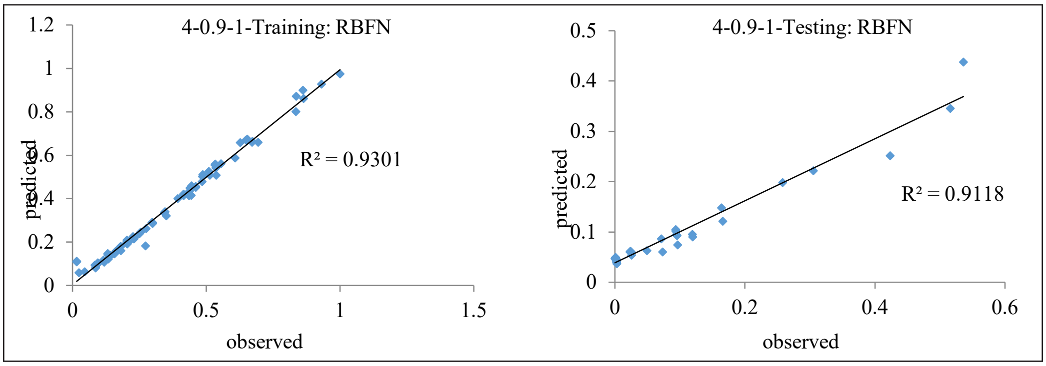
The graphs with best values for runoff from precipitation, maximum temperature, minimum temperature, evapotranspiration using BPNN with Log-sig transfer function at Loisingha shown in Figure 5. For Saintala watershed, the best value for runoff model is presented in Figure 6. The graphs below show how these best values results in the variation between the observed runoff and predicted runoff.



(a)

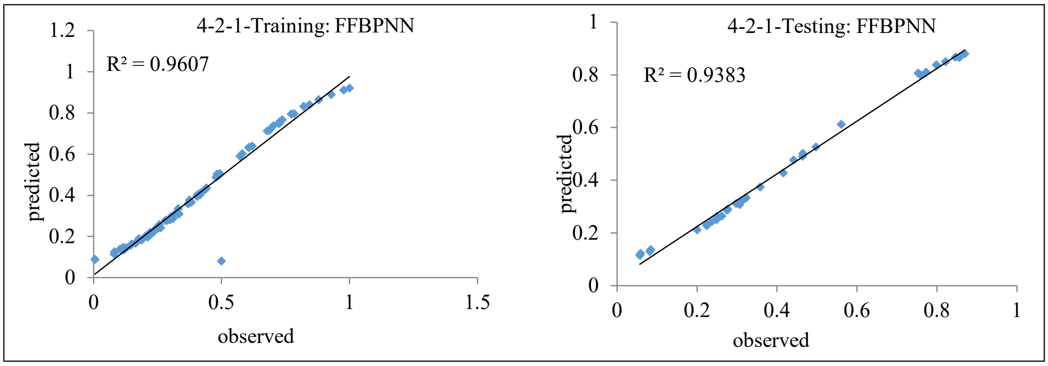


(b)

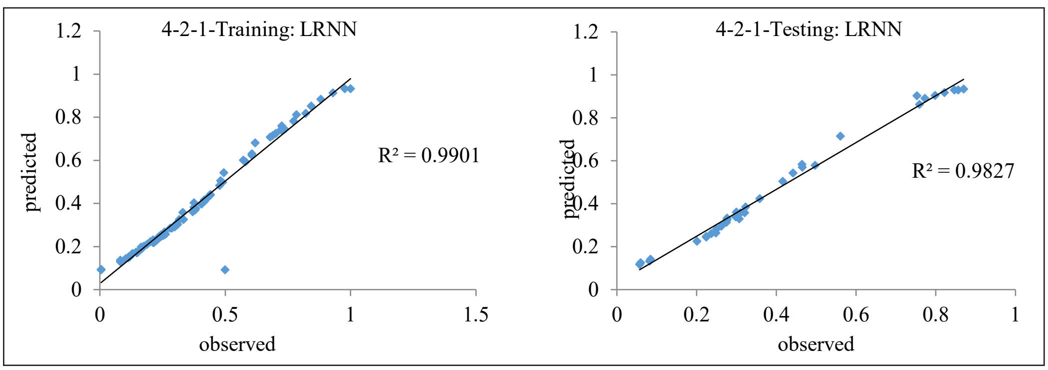


(c)

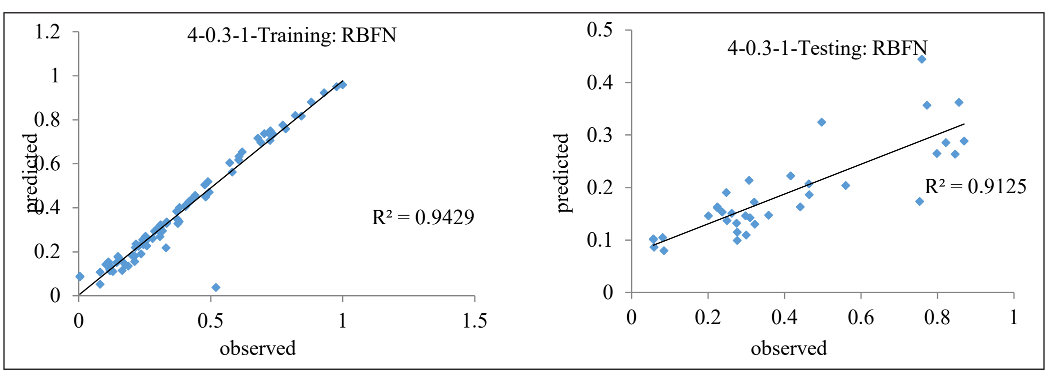
Figure 5. Best Observed V/s Predicted runoff model using BPNN, LRNN, and RBFN (Loisingha)



(a)



(b)



(c)

Figure 6. Best Observed V/s Predicted runoff model using BPNN, LRNN, and RBFN (Saintala)

Comparison of Model Performance for Two Watersheds

At Loisingha watershed among three neural networks with the evaluation criteria MSE, RMSE, and coefficient of determination LRNN performed best with architecture 4-9-1 following Tan-sig transfer function. At Saintala BPNN performed best among three networks with model architecture 4-3-1 using Purelin transfer function. The detailed result is tabulated below (Table 10). Since LRNN showed best efficiency the model would be utilized for predicting runoff of future uses nearest to the watershed and recommended for irrigation, and water resources department of Bolangir.

Table 10
Comparison of results for two watersheds

Scenario 2	Transfer Function	Tech-niques	Archi-tecture	MSE		RMSE		R^2	
				Training	Testing	Training	Testing	Training	Testing
P_t, T_{max}, T_{min}, E_t	Loisingha	BPNN	4-2-1 (Log-sig)	0.00463	0.00165	0.01591	0.03432	0.9662	0.9327
		LRNN	4-3-1 (Tan-sig)	0.00748	0.00336	0.02734	0.05796	0.9972	0.9621
		RBFN	4-0.9-1	0.00537	0.00314	0.02317	0.05589	0.9301	0.9118
	Saintala	BPNN	4-2-1 (Log-sig)	0.00278	0.00894	0.05174	0.09270	0.9607	0.9383
		LRNN	4-2-1 (Log-sig)	0.00632	0.00612	0.05130	0.07823	0.9901	0.9827
		RBFN	4-0.3-1	0.00214	0.04255	0.05304	0.03775	0.9429	0.9125

Assessment of Actual Runoff versus Simulated Runoff at Loisingha, and Saintala during Testing Phase

The variation of actual runoff vs. simulated or predicted runoff is revealed in Figure 7. Results shows that the estimated peak runoff were 306.2054 mm, 315.8574 mm, and 299.3439 mm for BPNN, LRNN, RBFN against the actual peak 328.3 mm for the watershed Loisingha, For watershed Saintala, the estimated peak runoffs were 344.5062 mm, 360.8081 mm, and 335.0335 mm for BPNN, LRNN, RBFN against the actual peak of 367.16 mm shown in Figure 8. This shows the significant potential of runoff and found to be useful for drought prone region with the predicted runoff index.

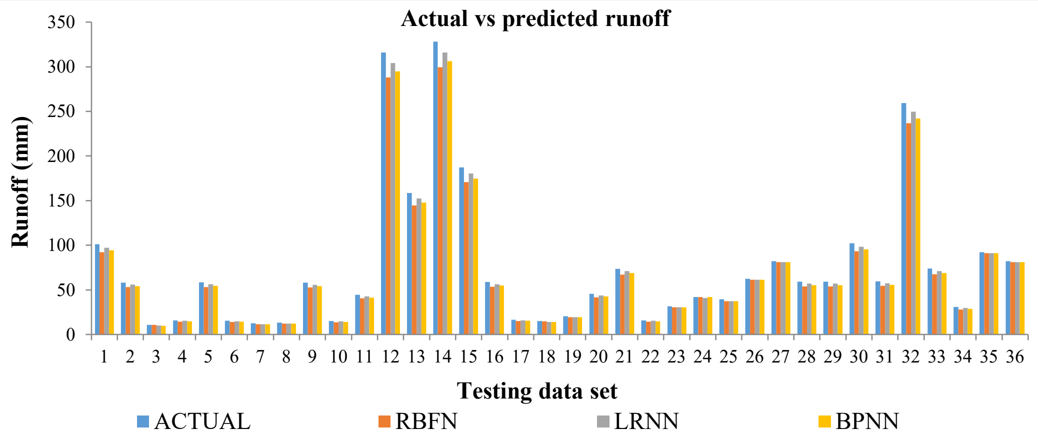


Figure 7. Actual v/s simulated runoff using BPNN, LRNN and RBFN at Loisingha in testing phase

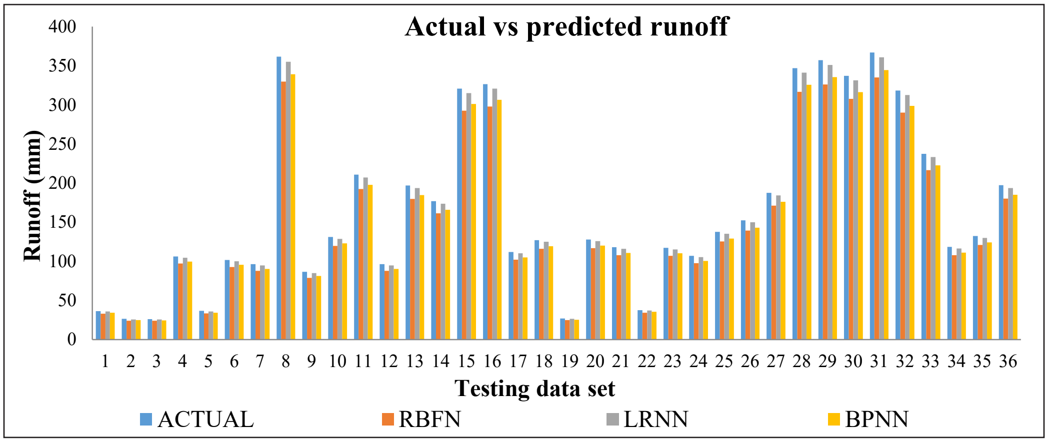


Figure 8. Actual v/s simulated runoff BPNN, LRNN and RBFN for Saintala in testing phase

CONCLUSIONS

Present study for predicting runoff is in fine agreement to model performance with evapotranspiration. Among two scenarios the prediction by evapotranspiration with all models performed best as compared to prediction without evapotranspiration. Overall performance with architecture 4-3-1 following Tan-sig transfer function, LRNN performed best. Model architecture 4-2-1 using Log-sig transfer function performed better with LRNN at Saintala. The best model performance was 0.9662 using BPNN, 0.9972 using LRNN and 0.9301 using RBFN at Loisingha. The influence of evapotranspiration was glowingly observed in watersheds for predicting runoff. Increase in evapotranspiration minimised the runoff potential for throughout the study area and *vice versa*. Since the area is within the region of scanty rainfall, the development of models will be helpful for assessing runoff. These results suggest the most suitable methods for developing environmental issues to estimate runoff in the two different watersheds of arid region. However, the combination technique needs to be investigated for improving integrated model techniques for future

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