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REAL TIME FLOOD FORECASTING AT KASOL (BHAKRA RESERVOIR) USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Forecasting flood in real time is one of the important non-structural measures of flood management to avoid loss of life and damage to properties. Engineers developed many models to issue real time forecasts at flood forecasting stations by using conventional methods. With the invention of supercomputers, many mathematical models have been developed and implemented for the forecasting of floods in real time. In the recent years, Artificial Neural Network (ANN) models have been successfully applied for real time flood forecasting because of its better performance and simplicity over the traditional models such as multiple linear regression and gauge to gauge correlation models. In this study, the development of an ANN model for flood forecasting in real time with lead of 1 day, 2 day, 3 day and 6 day for Sutlej basin up to Kasol site has been presented. The statistical parameters such as auto correlation, partial auto correlation and cross correlation of the series have been computed and used to select the input vector of the ANN model. The performance of the ANN models has been compared with MLR models and it has been found that ANN models for all the lead (1 day, 2 day, 3 day and 6 day) outperformed the MLR models. The sensitivity of transfer functions such as logsig and tansig in forecasting of discharge has been studied. The results based on the performance indices of the models indicate the possible implementation of the developed ANN model for forecasting the flood in real time with lead of 1 day, 2 day, 3 day, and 6 day at Kasol site on Sutlej River with reasonable accuracy.

Key words: *ANN models, Kasol, Real time flood forecasting, Sutlej basin*

INTRODUCTION

Flood forecasting has always been one of the most important issues in disaster management. Forecasting a river flow provides a warning of increasing water levels during floods and assists in regulating reservoir outflows during low river flows for better water resources management. To date, a wide variety of mathematical models have been developed and applied for flood forecasting. In the Indian context, the country experiences severe floods in perennial rivers of northern and middle India during the monsoon season (June to September) due to high intensity of rainfall in the catchment area. This calls for the development of a real time flood forecasting system to mitigate the damages caused by this natural hazard. Though conceptual mathematical models could be employed for this purpose, its development and calibration involves a number of physical parameters such as soil properties, land use, topographical features that interact in a complex fashion to be optimized, which warrants a large amount of historic data such as rainfall, wind velocity, humidity, temperature, solar radiation. In contrast, black box models are proven to produce good result from the input-output mapping when a detailed physical description of the process is not required. The country normally uses gauge-to-gauge correlation (CWC method) method to forecast the stream flow data (Central Water Commission, 1989), however, the method do not account for the nonlinearity in the river flow series. In recent years artificial neural network (ANN) models have been applied successfully for flood forecasting because of its ability to map any nonlinear function of given sufficient complexity. ANNs are proven to produce improved performance over other black box models such as auto regressive (AR), ARMA (Auto Regressive Moving Average) models in numerous modeling studies (Hsu et al., 1995; ASCE 2000a, b; Mayor and Dandy, 2000; Oyebode and Stretch (2018); Tealab, 2018; Poonia andTiwari, 2020; Tabbussum and Dar, 2020, Dtissibe et al., 2020). Many researchers have implemented ANN models to issue flood forecasts for basins ranging from small to large (Hsu et al., 1995; Thirumalaiah and Deo, 1998; Fernando and Jayawardena, 1998; Zealand et al., 1999; Tokar and Johnson, 1999; Atiya et al., 1999; Thirumalaiah and Deo, 2000; Toth and Brath, 2002; Kisi, 2005; Islam, 2010; Khosravi et al., 2012; Mitra et al., 2016; Poonia andTiwari, 2020; Tabbussum and Dar, 2020, Dtissibe et al., 2020). But they have not studied the effect of transfer functions in hidden layer in terms of forecasting capability of discharge values in real time. The main advantage of the ANN models over traditional models is that they do not require information about the complex nature of the underlying process under consideration to be explicitly described in mathematical form. This paper discusses the development of a real time flood-forecasting model using ANN at Kasol gauging site (Bhakra reservoir) of river Sutlej and presents capability of the transfer functions in forecasting of flood discharges in real time.

THE STUDY AREA

The Sutlej River rises in the lakes of Manasarovar and Rakshastal in the Tibetan Plateau at an elevation of about 4,572 *m* and forms one of the main tributaries of Indus

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River. The flow of Sutlej is generated mainly from snow and glaciers. After travelling 322 km up to Bhakra gorge, the flow enters into 225.55 *m* high straight gravity dam (Bhakra Dam/ Gobind Sagar reservoir) commissioned in the year 1963. The total catchment area of Sutlej River up to Bhakra dam is about 56,876 km^2 of which about 22,305 km^2 (76°10′ E to 79°10′ E and 30°45′ N to 33°15′ N) lies in India including whole catchment of the Spiti basin. The map of Sutlej basin up to Bhakra Dam (76° 24′ E and 31° 24′ N) showing the drainage network, location of Bhakra dam, gauging sites, Kasol, Suni and Rampur and few rain gauge stations is presented in Figure 1. The average rainfall in the catchment is 1140 *mm*. The Sutlej runoff basically consists of two parts, one part is derived from the melting of the snow and the other results from the rainfall in the catchment. The melting of snow is represented by the flow measured at Rampur gauging station. The monsoon is generally marked by high river flows and occasional floods in Sutlej. There are significant contributions from snow and glaciers into the stream flow of Sutlej and maximum during summer months. The Bhakra dam has controlled the devastating floods and benefits to irrigation and power have brought prosperity to the North India. This dam has a designed dead storage of 2431.81 Mm^3 and live storage of 7436.03 Mm^3; i.e., total storage of capacity 9867.84 Mm^3 (BBMB, 2003). It has enormous water spread area, extending over 168.35 km^2 at full reservoir level (515.11 *m*). Its tail touches a point about 12.87 *km* above Slapper village near Kasol. The index map of Bhakra reservoir shows the extend of the reservoir and the location of gauging station, Kasol (77° 18′ E and 32° 0′ N) is given in Figure 2.

The efficient operation of the Bhakra Dam is very important to avoid spill from Nangal Dam, a balancing reservoir downstream of Bhakra Dam, and inundation of downstream area of Nangal dam during monsoon season and to release

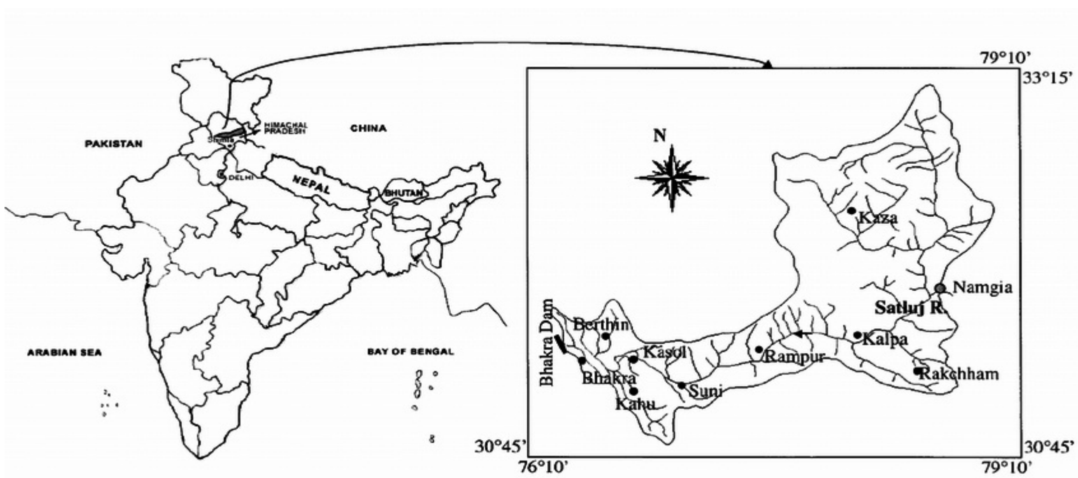

Fig. 1: Map of the Satluj basin (Indian part) up to Bhakra Reservoir with location of hydrometeorological stations (Singh and Jain, 2003)

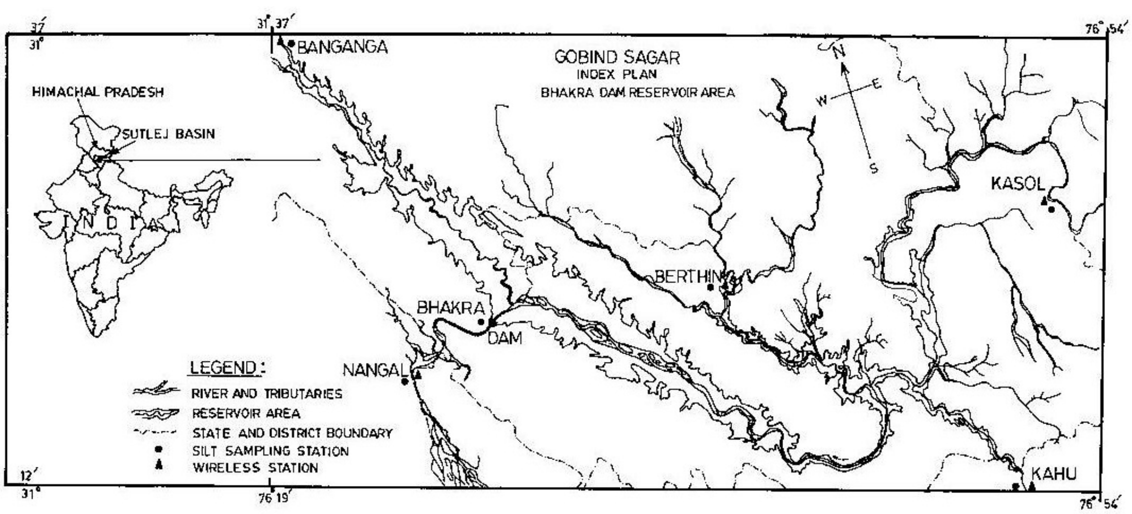

Fig. 2: **Index map of Bhakra reservoir**

the water for other purposes such as irrigation and power generation during the non monsoon season. So efficient operation of Bhakra dam warrants forecasts of the flow in real time into reservoir. Flood forecasts at Kasol gauging site is sufficient to operate the reservoir efficiently during monsoon and non monsoon season because it is located at tail end of the reservoir. Therefore, it is proposed to develop a flood-forecasting model using the Artificial Neural Networks (ANN) for the Sutlej basin up to Kasol.

ROLE OF ANN IN FLOOD FORECASTING

A number of studies have been reported that investigate the potential of neural networks in flood forecasting. Most of them have used antecedent rainfall and runoff information to get an accurate forecast for the future river flows. Comprehensive review of ANN applications to flood forecasting can be seen in ASCE (2000a, b), Mayor and Dandy (2000), Oyebode and Stretch (2018), Tealab (2018). Some of such applications are Portugal (1995), Minns and Hall (1996), See et al (1997), Fernando and Jayawardena (1998), Thirumalaiah and Deo (1998), Danh et al (1998), Zealand et al (1999), Atiya et al (1999), Tokar and Johson (1999), Thirumalaiah and Deo (2000), Elshorbagy et al (2000), Toth and Brath (2002), Kisi (2005), Islam (2010), Khosravi et al. (2012), Mitra et al. (2016), Poonia andTiwari (2020) Tabbussum and Dar (2020) and Dtissibe et al. (2020). These studies report that ANN outperforms the traditional forecasting techniques such Auto Regressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), and many conceptual models.

ANN – AN OVERVIEW

ANNs are a form of computing inspired by the functioning of the brain and nervous system and are discussed in detail in a number of hydrologic papers. For example, Portugal, 1995; Minns and Hall, 1996; See et al, 1997; Danh et al, 1998; Zealand et al, 1999; ASCE, 2000a,b; Maier and Dandy, 2000; Elshorbagy, 2000; Toth and Brath, 2002; Kisi 2005; Islam, 2010; Khosravi et al., 2012, Mitra et al., 2016; Poonia andTiwari, 2020; Tabbussum and Dar, 2020; and Dtissibe et al., 2020. The architecture of a feed forward ANN can have many layers where a layer represents a set of parallel neurons. The basic structure of ANN usually consists of three layers: the input layer, where the data are introduced to the network; the hidden layer or layers, where data are processed; and the output layer, where the results of given outputs are produced. The neurons in the layers are interconnected by strength called weights. A typical three-layered feed forward ANN is shown in Fig. 3

In general, a neuron can have n inputs, labeled from 1 through *n*. For example neuron 3 in the hidden layer shown in Fig. 3, n= 2. In addition, each neuron has an input that is equal to 1.0, called *bias*. Each neuron *j* receives information from every node *i* in the pervious layer. A weight (w_{ji}) is associated with each input (x_i) to node *j*. The effective incoming information (NET_j) to node *j* is the weighted sum of all incoming information, otherwise known as the net input, and is computed as:

$$NET_j = \sum_{i=0}^{n} w_{ji} x_i \qquad 1$$

where x_0 and w_{j0} are called as the bias term (x_0 = 1.0) and the bias respectively. Equation 1 applies to the nodes in the output layer and hidden layer(s). The weighted sum of input information is passed through an activation function, called transfer function, to produce the output from the neuron. The transfer function introduces some nonlinearity in the network, which helps in capturing the nonlinearity present in the function being mapped. The commonly employed transfer function is the *logsigmoidal* function (ASCE, 2000a) and is given as follows:

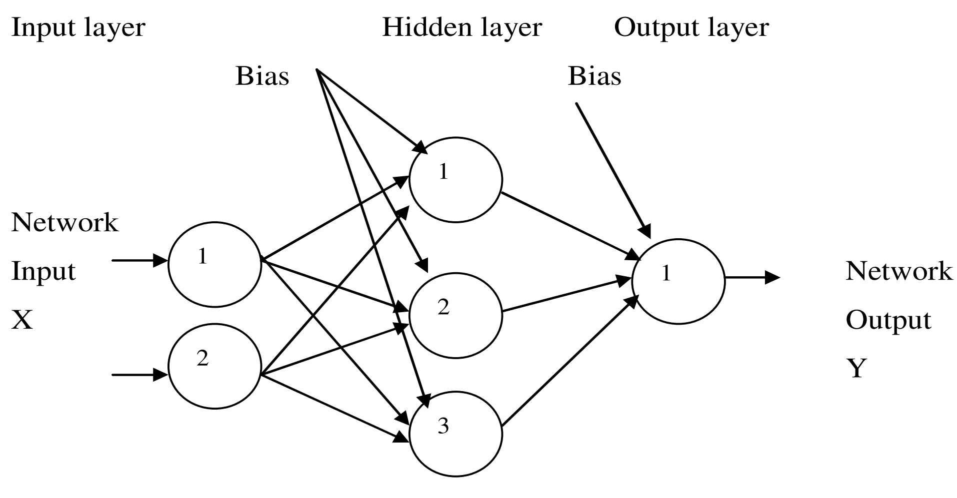

Fig. 3: A Typical Three-Layer Feed Forward ANN (ASCE, 2000a)

$$OUT_j = \frac{1}{1+e^{-NET_j}} \qquad 2$$

Alternatively, *tansigmoidal* function can also be used as transfer function to better results of the output from hidden neuron and is given as follows:

$$OUT_J = \frac{2}{\left(1+e^{-2*NET_J}\right)} - 1 \qquad 3$$

The interconnected weights are adjusted using a learning algorithm such that the output from the ANN model is very close to the observed values by minimizing the error through a mathematically formulated procedure. This procedure is called training of network.

Using a set of examples from a given problem domain, comprising inputs and their corresponding outputs, an ANN model can be trained to learn the relationship between the input-output pairs. The feed forward ANN is generally adapted in all studies because of its applicability to a variety of different problems (Hsu et al., 1995). However, there are no guidelines in developing an effective ANN architecture, though some researchers have reported suggestions that can be implemented while developing an ANN model. For instance, Maier and Dandy (2000) report that not more than one hidden layer is required in feed forward networks because a three-layer network can generate arbitrarily complex decision regions. Also, the appropriate input vector to the ANN model can be identified according to the procedure of Sudheer et al. (2000).

The input values should be normalised to the range between 0 and 1 and -1 and 1 before passing into a neural network since the output of *logsigmoidal* and *tansigmoidal* functions is bound between 0 and 1 and -1 and 1 respectively. Minns and Hall, 1996, Dawson and Wilby (1998), Sajikumar and Thandaveswara (1999), and Burian et al (2001) emphasised the importance of the normalisation of data and gave the procedure to normalise. The output from the ANN should be denormalised to provide meaningful results. In this study, the inbuilt functions of MATLAB *mapstd* and *mapminmax* have been used to normalize the data set between 0 and 1 and -1 and 1 respectively. The *logsigmoidal* transfer function is used with *mapstd* inbuilt function and *tansigmoidal* transfer function is used with *mapminmax* inbuilt function.

Training a network is a procedure during which an ANN processes training set (input-output data pairs) repeatedly, changing the values of its weights, according to a predetermined algorithm and the environment in which the network is embedded. The main objective of training (calibrating) a neural network is to produce an output vector $Y = (y_1, y_2, ..., y_p)$ that is as close as possible to the target vector (variable of interest or forecast variable) $T = (t_1, t_2, ..., t_p)$ when an input vector $X = (x_1, x_2, ..., x_p)$ is fed to the ANN. In this process, weight matrices W and bias vectors V are determined by minimizing a predetermined error function as explained as follows:

$$E = \sum_P \sum_p (y_i - t_i)^2 \qquad 4$$

where t_i is a component of the desired output T; y_i is the corresponding ANN output; p is the number of output nodes; and P is the number of training patterns.

Back propagation is the most popular algorithm used for the training of the feed forward ANNs (Hsu et al, 1995; Dawson and Wilby, 1998; Thirumalaiah and Deo, 1998; Sajikumar and Thandaveswara, 1999; Tokar and Jhonson, 1999; Zealand et al, 1999; Thirumalaiah and Deo, 2000; ASCE, 2000a; Elshorbagy et al, 2000; Maier and Dandy, 2000; Burian et al, 2001; Toth and Brath, 2002; Kisi 2005; Islam, 2010; Khosravi et al., 2012, Mitra et al., 2016; Poonia andTiwari, 2020; Tabbussum and Dar, 2020; and Dtissibe et al., 2020.). Each input pattern of the training data set is passed through the network from the input layer to output layer. The network output is compared with the desired target output, and an error is computed based the equation 4. This error is propagated backward through the network to each neuron, and the connection weights are adjusted based on the equation

$$\Delta w_{ij}(n) = -\varepsilon * \frac{\partial E}{\partial w_{ij}} + \alpha * \Delta w_{ij}(n-1) \qquad 5$$

where $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are weight increments between node *i* and *j* during *n*th and *(n-1)*th pass, or epoch (ASCE, 2000a). A similar equation is written for correction of bias values. In the equation 5, ε and α are called learning rate and momentum respectively. The momentum factor can speed up training in very flat regions of the error surface and help prevent oscillations in the weights. A learning rate is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima. The literature by Rumelhart et al, 1986 can be referred for the details of the algorithm. In this training, gradient descent with momentum (*traingdm*) is used to optimize the interconnected weights and biases of the hidden and output layers.

Performance evaluation of ANN model

The whole data length is divided into three, calibration (training) (1.1.1993 to 30.04.2005), validation (1.1.1989 to 31.12.1992) and testing (1.9.1984 to 31.12.1988) of artificial neural network models. The data from 1.1.1993 to 30.04.2005 have been selected for the training of the ANN models for lead periods – 1 day, 2 day, 3 day, 6 day since they contain extreme values of rainfall and discharge and it is useful in issuing forecasts in real time with new data set in future. The performance during calibration, validation and testing is evaluated by performance indices such as root mean square error (RMSE), model efficiency (Nash and

Sutcliffe, 1970) and coefficient of correlation (R). They are defined as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{K}(t-y)^2}{K}} \quad 6$$

$$\text{Efficiency} = 1 - \frac{\sum(t-y)^2}{\sum(t-\bar{t})^2} \quad 7$$

$$\text{Coefficient of Correlation} = \frac{\sum TY}{\sqrt{\sum T^2 \sum Y^2}} \quad 8$$

where K is the number of observations; t is the observed data; y is computed data; $T = t - \bar{t}$ in which $\bar{t}$ is the mean of the observed data; and $Y = y - \bar{y}$ in which $\bar{y}$ is the mean of the computed data.

MODEL DEVELOPMENT

For the current application, daily rainfall data (1.1.1984 to 30.04.2005) for Kalpa, Rampur, Rackchham, Berthin, Bhakra, Kahu, Kasol, Kaza, Namagia and Suni are available for the period from 1984 to 2005. The daily discharge data for three gauging stations at Rampur, Suni and Kasol are also available for the same period. These rain gauge and river gauge stations are marked in Fig 1. The ANN models have been developed to forecast the river flow at Kasol for 1, 2, 3 and 6 days in advance in the current study. The details of the model development are described in the following sections.

Selection of Input

The ANN model for the real time flood forecasting is normally developed using the antecedent rainfall and discharge values of upstream stations as input vector. Determining the number of antecedent rainfall and discharge values involves finding the lags of rainfall and discharge values that have significant influence on the forecasted flow. These influencing values corresponding to different lags can be very well established through statistical analysis of the data series. The input vector is selected generally by trial and error method; however, Sudheer et al. (2002) have presented a statistical procedure that avoids the trial and error procedure. They reported that the statistical parameters such as auto correlation function (ACF), partial auto correlation function (PACF) and cross correlation function (CCF) can be used for this purpose. It is evident from Fig. 4, which presents the ACF plot of river flow at Kasol, that the runoff series at Kasol is autoregressive. The PACF of flow series at Kasol (Fig 5) with 95% confidence level gives potential antecedent runoff values that have influence on the runoff value at the current period. It can be seen from the Fig 5 that the runoff series with 1 lag should be included in the input vector. The PACF of the runoff series at Kasol with 95 % confidence levels and CCF of runoff series at Kasol between rainfall at Kalpa, Rampur, Rackchham, Berthin, Bhakra, Kahu, Kasol, Kaza, Namagia and Suni and runoff series at Rampur and Suni suggest the input vector to the ANN model. From the Fig. 6-15 the cross correlation between the rainfall at Kalpa, Rampur, Rackchham, Berthin, Bhakra, Kahu, Kasol, Kaza, Namagia and Suni and runoff at Kasol indicates that the rainfall at lag 1 and 2 lags influence the runoff. In the same way, the figures 16 and 17 present the influencing lags of runoff series at Rampur and Suni. On the basis of PACF and CCF of the data series, the following input vector is selected for neural network training.

$Q_{kasol,t} = f(R_{kalpa,t-1}, R_{rampur,t-1}, R_{rackcham,t-1}, R_{berthin,t-1}, R_{bhakra,t-1}, R_{kahu,t-1}, R_{kasol,t-1}, R_{kaza,t-2}, R_{namagia,t-1}, R_{suni,t-1}, Q_{rampur,t-1}, Q_{suni,t-1}, Q_{kasol,t-1})$ 9

In which Q and R are discharge and rainfall values respectively

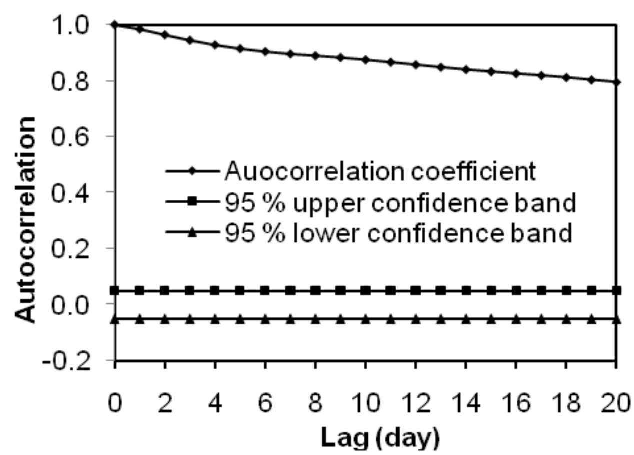

Fig. 4: The autocorrelation of the runoff series at Kasol

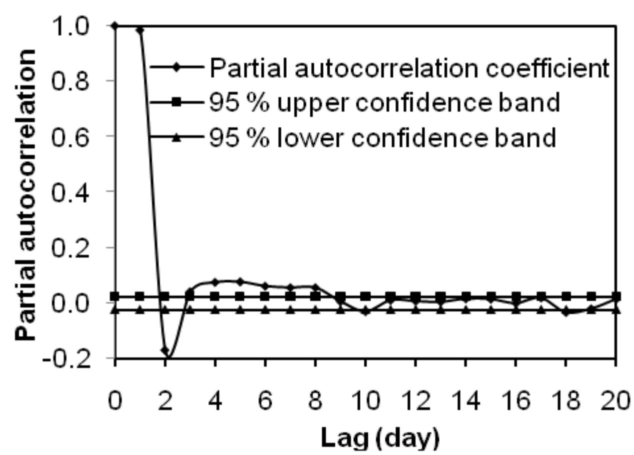

Fig. 5: The partial autocorrelation of the runoff series at Kasol

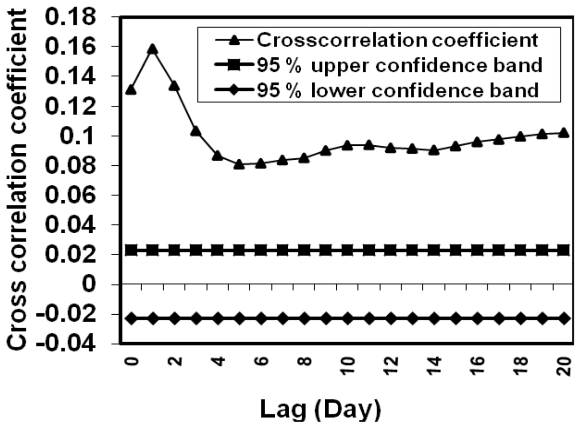

Fig. 6: The cross correlation of rainfall at Kalpa with runoff at Kasol

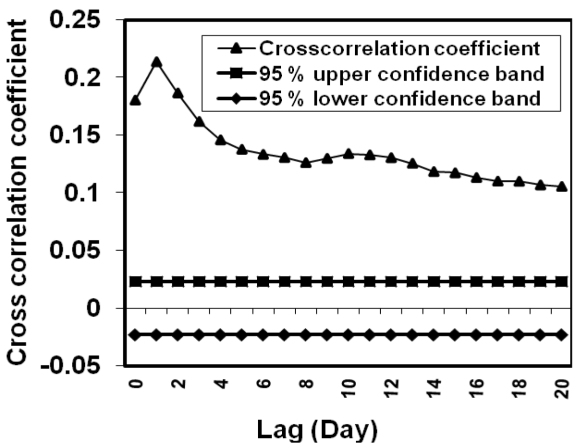

Fig. 7: The cross correlation of rainfall at Rampur with runoff at Kasol

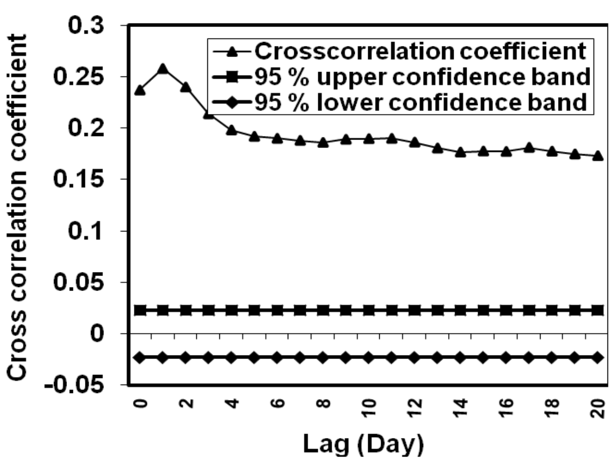

Fig. 8: The cross correlation of rainfall at Rackchham with runoff at Kasol

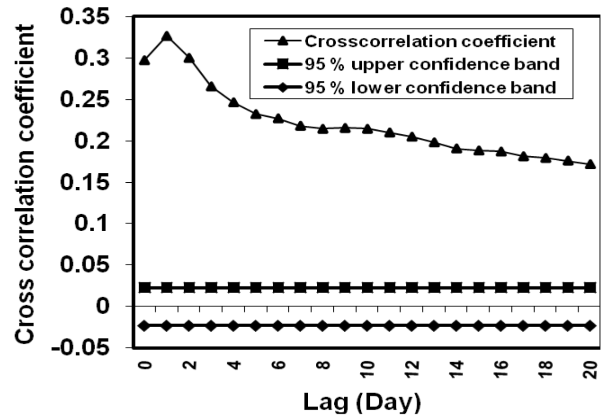

Fig. 9: The cross correlation of rainfall at Berthin with runoff at Kasol

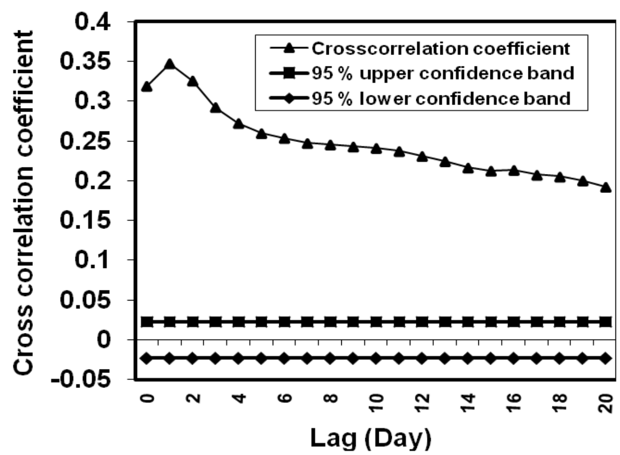

Fig. 10: The cross correlation of rainfall at Bhakra with runoff at Kasol

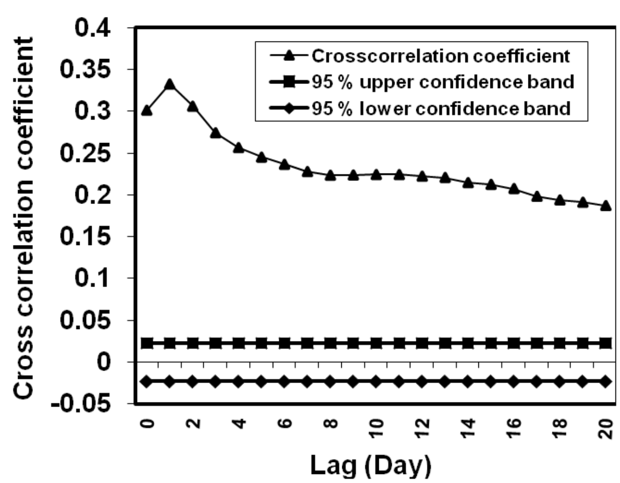

Fig. 11: The cross correlation of rainfall at Kahu with runoff at Kasol

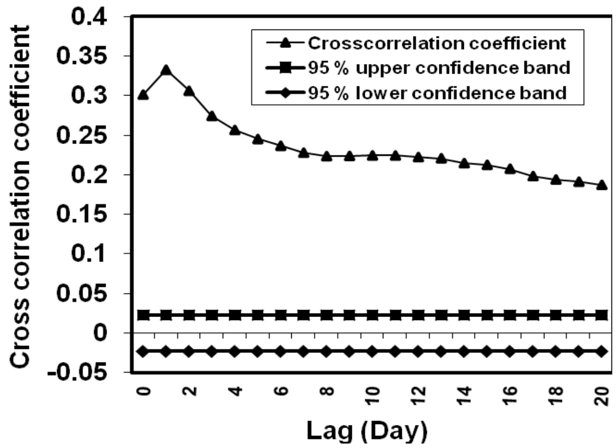

Fig. 12: The cross correlation of rainfall at Kasol with runoff at Kasol

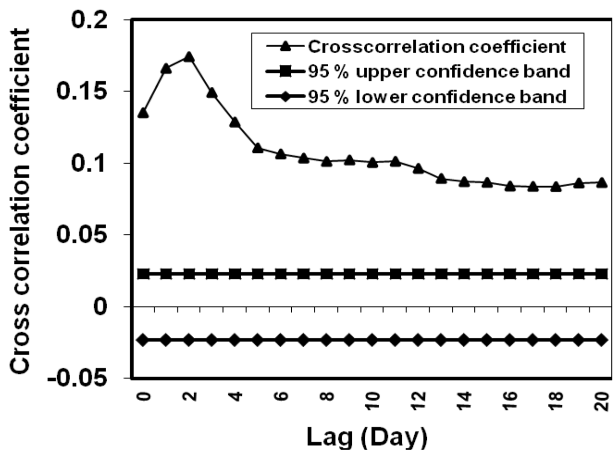

Fig. 13: The cross correlation of rainfall at Kaza with runoff at Kasol

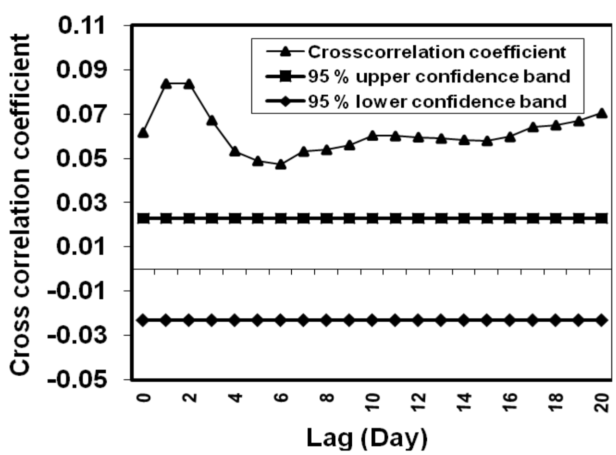

Fig. 14: The cross correlation of rainfall at Namagia with runoff at Kasol

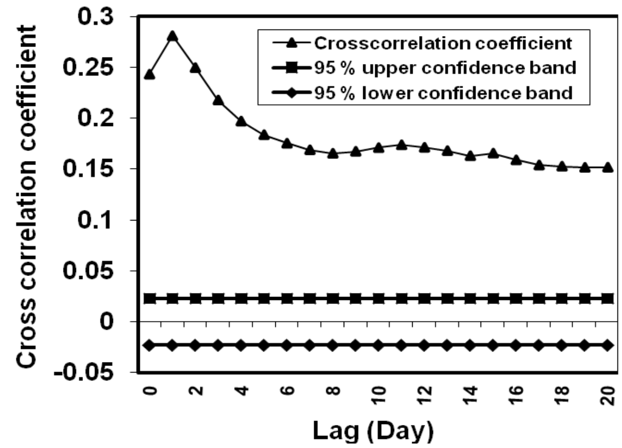

Fig. 15: The cross correlation of rainfall at Suni with runoff at Kasol

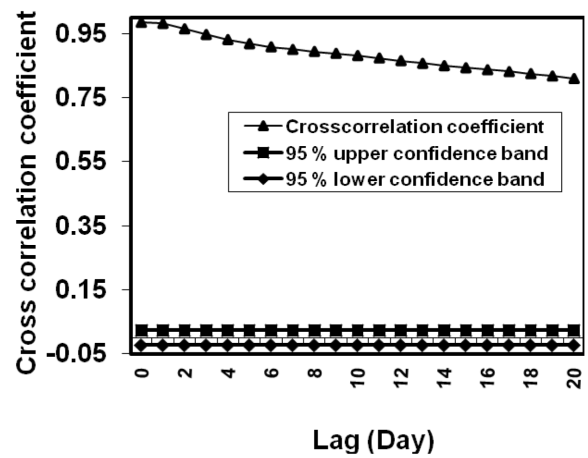

Fig. 16: The cross correlation of runoff at Rampur with runoff at Kasol

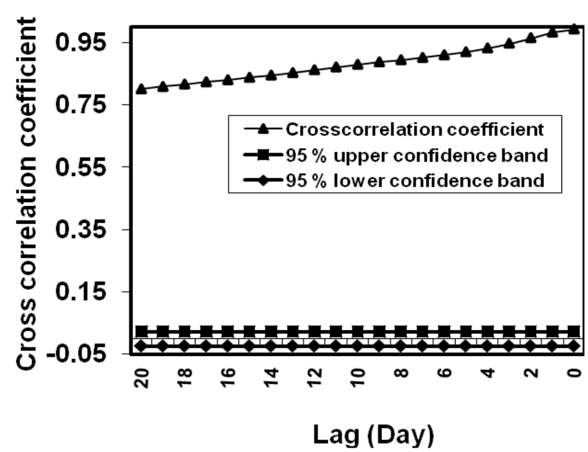

Fig. 17: The cross correlation of runoff at Suni with runoff at Kasol

ANN Model Training

The ANN model has been trained using back propagation algorithm. The lead-times considered in the model development for flood forecasting in real time are 1 day, 2 day, 3 day and 6 days. The software used for the training of the model is MATLAB (The Mathworks, Inc., 2007b). The whole data set is divided into three parts. The data set from 01.01.1993 to 30.04.2005, 01.01.1989 to 31.12.1992 and 01.09.1984 to 31.12.1988 are considered for calibration, validation and testing of the ANN models respectively. The ANN models have been developed for all the lead periods using both *logsigmoidal* and *tansigmoidal* transfer functions in the hidden layer. The transfer function used in the output layer is *purelinear*. The number of the hidden neurons in the hidden layer is found by a trail and error procedure, and the number of neurons is increased from 1 to 15 for all the lead periods of 1 day, 2 day, 3 day and 6 day for both *logsigmoidal* and *tansigmoidal* transfer functions. 5 neurons in general for both the transfer functions in the hidden layer are found to be optimum. Optimum neurons in the hidden layer have been arrived at by comparing the performance indices during calibration, validation and testing all together. Increase in hidden neurons has certainly increased the performance in forecasting marginally during calibration but performance during validation and testing has drastically deteriorated after 5 numbers of hidden neurons. The convergence for all models with both the transfer functions and 5 hidden neurons in general has been achieved from 130 to 426 epochs at a mean square error of 0.0001.

MLR models

Multiple Linear Regression (MLR) models have been developed for the forecasting of flood at Kasol for lead of 1 day, 2 day, 3 day and 6 day using the data and combination of input vector considered in the development of ANN models for the same lead periods. The equation of MLR models for the lead of 1 day, 2 day, 3 day and 6 day are represented by

1. **One day lead**

$$Q_{kasol,t+1} = -1.46R_{kalpa,t-1}+0.51R_{rampur,t-1}+2.29R_{rackcham,t-1}-0.10R_{berthin,t-1}+0.26R_{bhakra,t-1}+0.47R_{kahu,t-1}+0.32R_{kasol,t-1}+0.34R_{kaza,t-2}+4.09R_{namagia,t-1}-0.12R_{suni,t-1}+0.40Q_{rampur,t-1}+0.57Q_{suni,t-1}+0.11Q_{kasol,t-1}+13.49 \quad (10)$$

2. **Two day lead**

$$Q_{kasol,t+2} = -2.99R_{kalpa,t-1}+0.50R_{rampur,t-1}+1.69R_{rackcham,t-1}-0.19R_{berthin,t-1}-0.00R_{bhakra,t-1}-0.05R_{kahu,t-1}+0.72R_{kasol,t-1}-0.36R_{kaza,t-2}+4.05R_{namagia,t-1}-0.60R_{suni,t-1}+0.35Q_{rampur,t-1}+0.71Q_{suni,t-1}+0.02Q_{kasol,t-1}+21.28 \quad (11)$$

3. **Three day lead**

$$Q_{kasol,t+3} = -3.30R_{kalpa,t-1}+0.37R_{rampur,t-1}+1.40R_{rackcham,t-1}-0.11R_{berthin,t-1}-0.08R_{bhakra,t-1}-0.34R_{kahu,t-1}+0.74R_{kasol,t-1}-2.07R_{kaza,t-2}+3.33R_{namagia,t-1}-0.57R_{suni,t-1}+0.30Q_{rampur,t-1}+0.80Q_{suni,t-1}-0.04Q_{kasol,t-1}+27.21 \quad (12)$$

4. **Six day lead**

$$Q_{kasol,t+6} = -1.66R_{kalpa,t-1}+0.77R_{rampur,t-1}+0.37R_{rackcham,t-1}-1.05R_{berthin,t-1}+0.21R_{bhakra,t-1}-0.36R_{kahu,t-1}+0.58R_{kasol,t-1}-2.52R_{kaza,t-2}+2.50R_{namagia,t-1}-0.97R_{suni,t-1}+0.30Q_{rampur,t-1}+0.88Q_{suni,t-1}-0.14Q_{kasol,t-1}+38.37 \quad (13)$$

The forecasted values of discharge have been compared with observed discharge for 1 day, 2 day, 3 day and 6 day lead periods for both the ANN and MLR models using performance indices during calibration, validation and testing. The results of ANN models have been compared with the MLR models using performance indices to find out the quality of ANN models in forecasting of discharge values for the all lead periods.

RESULTS AND DISCUSSIONS

The model forecasted discharge during calibration, validation and testing for 1 day, 2 day, 3 day and 6 day lead periods for *logsigmoidal* and *tansigmoidal* transfer function are presented in Figures 18 to 41 along with the corresponding observed flow series. The visual inspection of the forecasted flood series clearly demonstrates the potential of the developed ANN model in forecasting the flow for all lead periods, 1 day, 2 day, 3 day and 6 day at Kasol. It is also observed from scatter plot that the forecasted values are spread away from the linear line as the lead periods are increased from 1 to 6. This clearly indicates the less forecasting accuracy for higher lead periods. The extreme values are under forecasted for all lead periods which are important for issuing flood warnings. The results have been further analyzed using statistical indices. The results of the best ANN models for lead periods of 1 day, 2 day, 3 day and 6 day with *logisigmoidal* function during calibration, validation and testing in terms of various statistical indices are presented in the Table 1. The results of the best ANN models for lead periods of 1 day, 2 day, 3 day and 6 day with *tansigmoidal* function during calibration, validation and testing in terms of various statistical indices are presented in the Table 2. The results of the best MLR models for lead periods of 1 day, 2 day, 3 day and 6 day during calibration, validation and testing in terms of various statistical indices are presented in the Table 3.

The above results indicate that the developed ANN model structure simulates the nonlinearity in the data with reasonable accuracy. The high coefficient of correlation during the calibration, validation and testing for 1 day lead with *logsigmoidal* transfer function indicates that explained variance is high and the developed ANN model is good to estimate the forecasts with less error. The RMSE, which is a measure of the residual variance, during calibration is very low compared to the mean flow (404.8 cumecs) for 1 day lead. However during the validation and test of the model

Table 1: Comparison of results among calibration, validation and testing of the ANN models for 1 day, 2 day, 3 day and 6 day lead periods with *logsigmoidal* function

Lead period	ANN Structure & Epochs	Calibration			Validation			Testing		
		CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs
1 day	13-5-1, 270	0.98	95.46	79.17	0.97	94.46	100.66	0.96	92.98	111.47
2 day	13-5-1, 130	0.96	92.74	100.11	0.96	91.50	124.61	0.95	90.11	132.23
3 day	13-5-1, 252	0.95	90.55	114.22	0.95	89.74	136.96	0.93	87.01	151.56
6 day	13-5-1, 159	0.93	85.53	141.32	0.92	83.67	172.75	0.91	82.42	176.27

Table 2 : Comparison of results among calibration, validation and testing of the ANN models for 1 day, 2 day, 3 day and 6 day lead periods with *tansigmoidal* function

Lead period	ANN Structure & Epochs	Calibration			Validation			Testing		
		CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs
1 day	13-5-1, 243	0.98	95.43	79.43	0.97	94.93	96.23	0.97	93.23	109.46
2 day	13-4-1, 130	0.96	92.53	101.55	0.96	92.47	117.13	0.95	90.07	132.53
3 day	13-5-1, 154	0.95	90.52	114.37	0.95	89.89	135.95	0.93	87.70	153.34
6 day	13-6-1, 426	0.93	85.68	140.49	0.91	83.57	173.30	0.91	82.69	174.92

Table 3 : Comparison of results among calibration, validation and testing of the MLR models for 1 day, 2 day, 3 day and 6 day lead periods

Lead period	Calibration			Validation			Testing		
	CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs	CORR Coeff	EFF %	RMSE cumecs
1 day	0.97	93.92	91.60	0.98	94.91	96.44	0.97	93.12	110.30
2 day	0.95	90.68	113.40	0.96	91.50	124.68	0.94	88.70	141.34
3 day	0.94	88.17	127.79	0.94	88.35	145.92	0.92	85.32	161.09
6 day	0.91	82.84	153.92	0.90	81.55	183.68	0.90	80.67	184.86

for 1 day lead, it slightly gets deteriorated as can be seen from the Table 1. The model efficiency is also high during calibration, validation and testing for 1 day lead period. The RMSE for higher lead periods during calibration, validation and testing are increasing but they are very low compared to mean flow (404.8 cumecs). The performance indices during calibration, validation and testing are marginally deteriorated as the lead periods are increased from 1 day to 2 day, 3 day and 6 day. This deterioration might have been caused by more number of the extreme events present in the validation and testing data that caused high skewness in the series (Sudheer et al., 2003). The error in forecasting of extreme values for higher lead periods is more but still it is under acceptable accuracy. The performance indices during calibration, validation and testing for lead periods 1 day, 2 day, 3 day and 6 day with *tansigmoidal* are almost same or less different to the performance indices for corresponding lead periods with *logsigmoidal* function and the same can be seen from Table 2. It suggests that any one of two transfer functions could be used for developing the ANN models for issuing forecasts for lead periods of 1 day, 2 day, 3 day and 6 day at Kasol. The performance indices for MLR models for lead periods of 1 day, 2 day, 3 day and 6 day are compared with the performance indices of ANN models with *logsigmoidal* and *tansigmoidal* transfer functions for the corresponding lead periods and it clearly indicates that ANN models with *logsigmoidal* and *tansigmoidal* transfer functions outperformed MLR models for all the lead period in forecasting the flood values (Table 3).

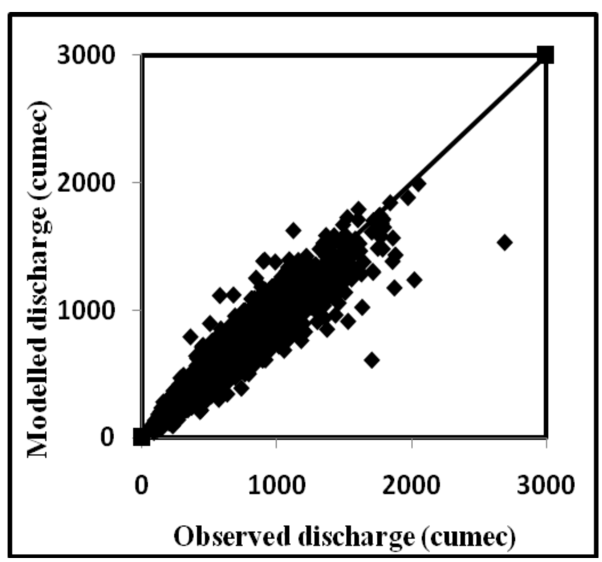

Fig. 18: Calibration result of ANN model (1 day lead, *logsigmoidal*)

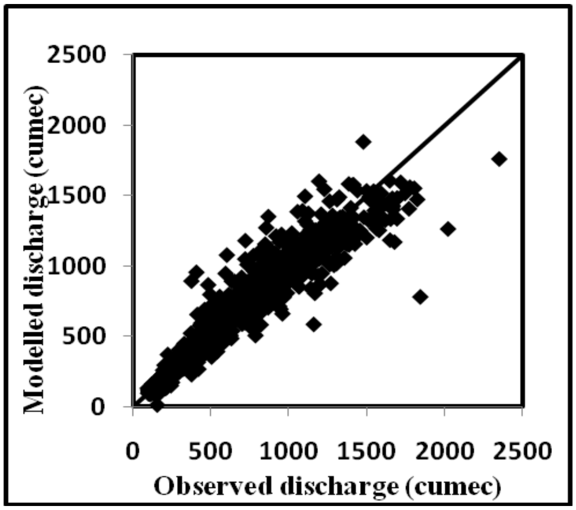

Fig. 19: Validation result of ANN model (1 day lead, *logsigmoidal*)

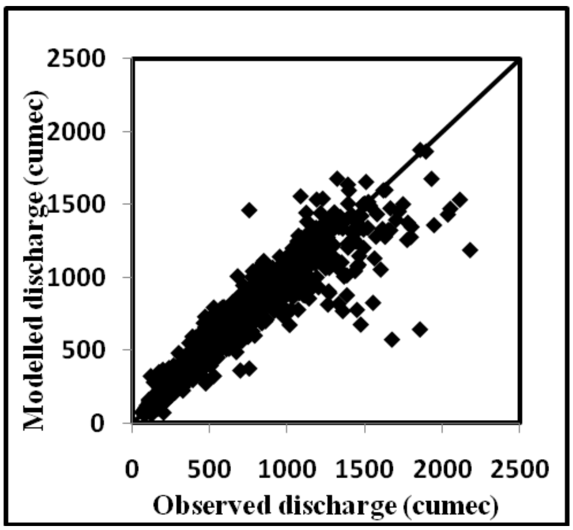

Fig. 20: Testing result of ANN model (1 day lead, *logsigmoidal*)

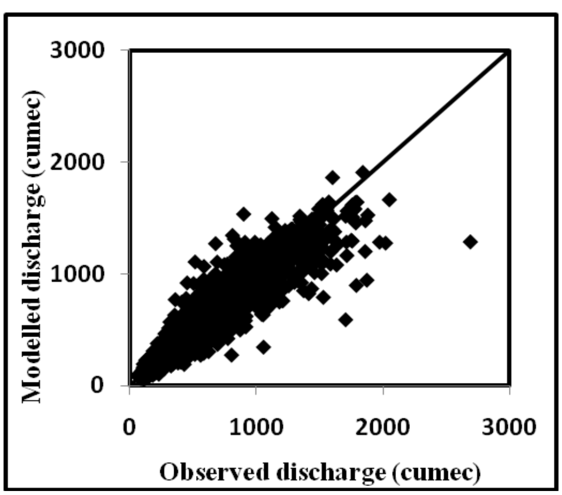

Fig. 21: Calibration result of ANN model (2 day lead, *logsigmoidal*)

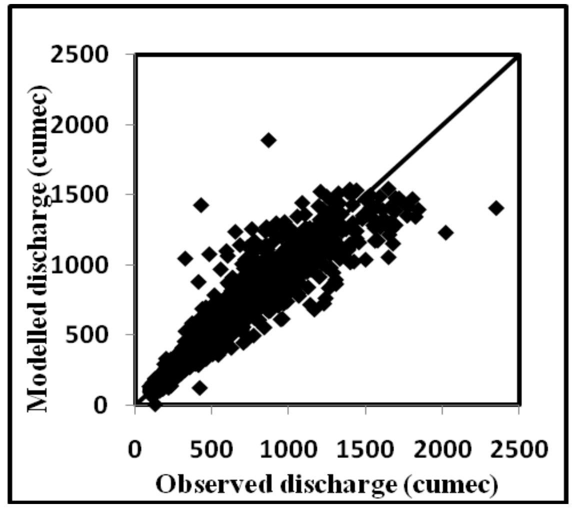

Fig. 22: Validation result of ANN model (2 day lead, *logsigmoidal*)

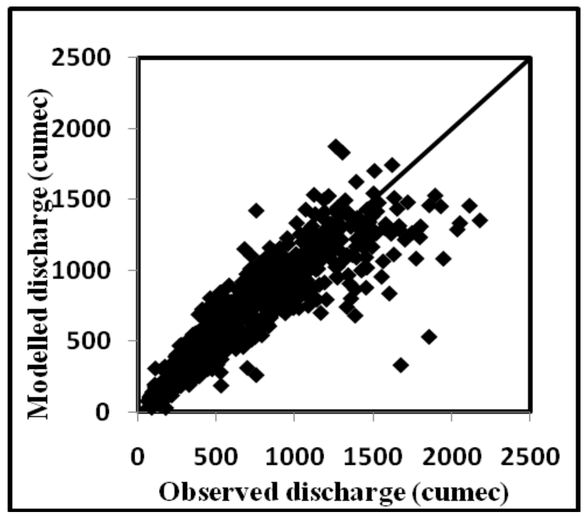

Fig. 23: Testing result of ANN model (2 day lead, *logsigmoidal*)

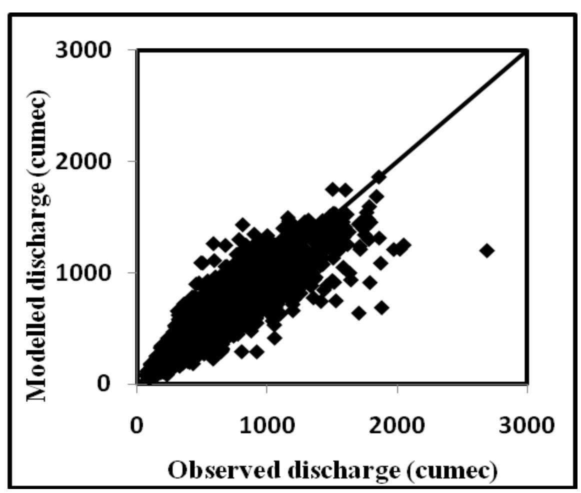

Fig. 24: Calibration result of ANN model (3 day lead, *logsigmoidal*)

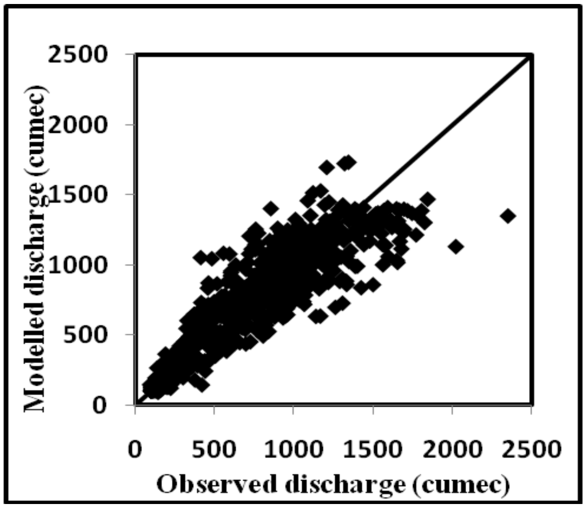

Fig. 25: Validation result of ANN model (3 day lead, *logsigmoidal*)

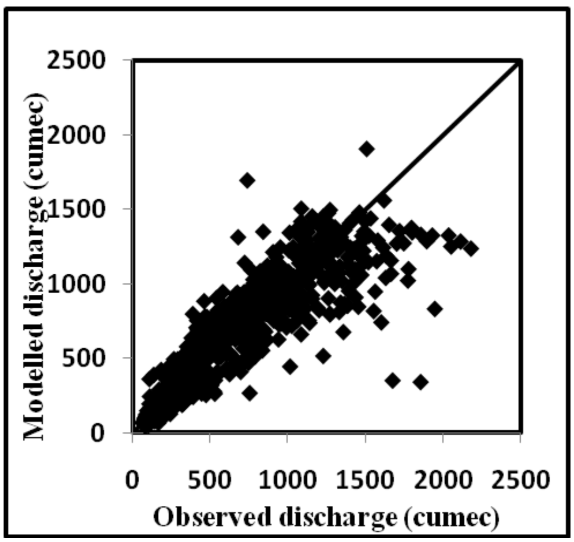

Fig. 26: Testing result of ANN model (3 day lead, *logsigmoidal*)

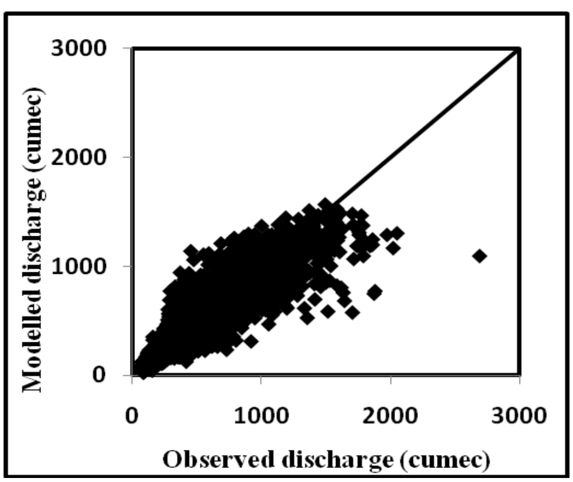

Fig. 27: Calibration result of ANN model (6 day lead, *logsigmoidal*)

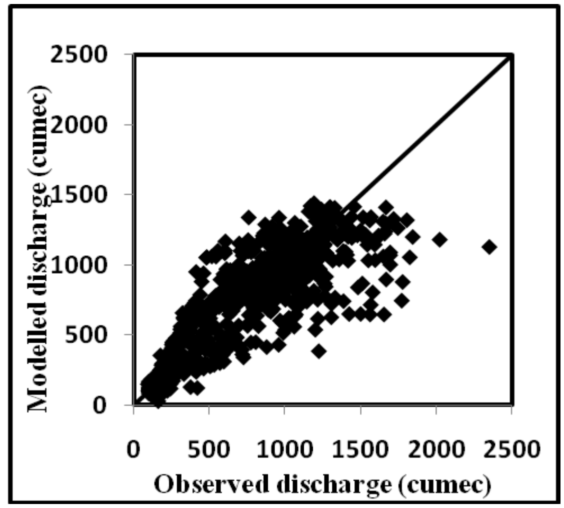

Fig. 28: Validation result of ANN model (6 day lead, *logsigmoidal*)

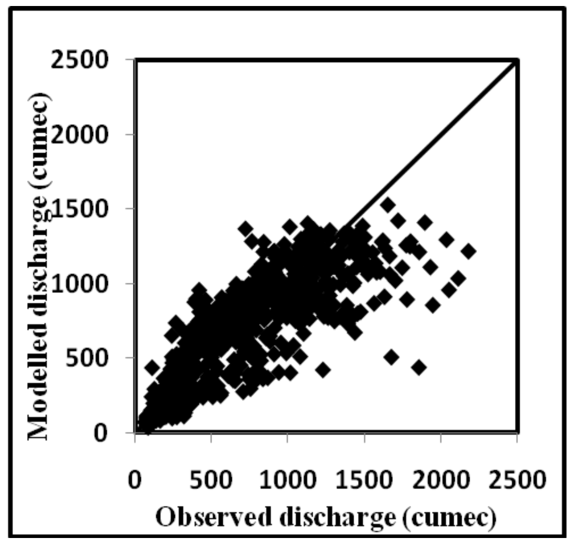

Fig. 29: Testing result of ANN model (6 day lead, *logsigmoidal*)

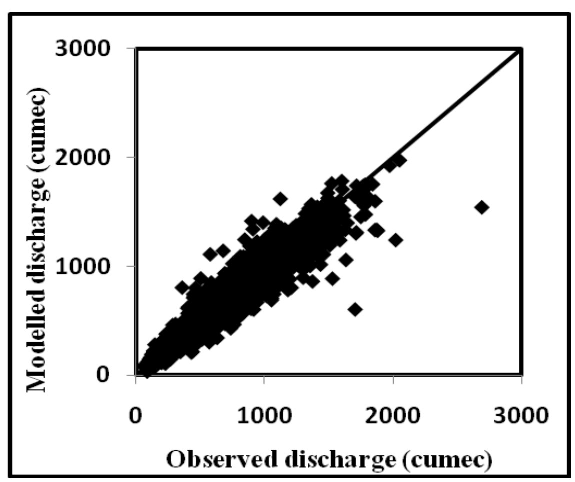

Fig. 30: Calibration result of ANN model (1 day lead, *tansigmoidal*)

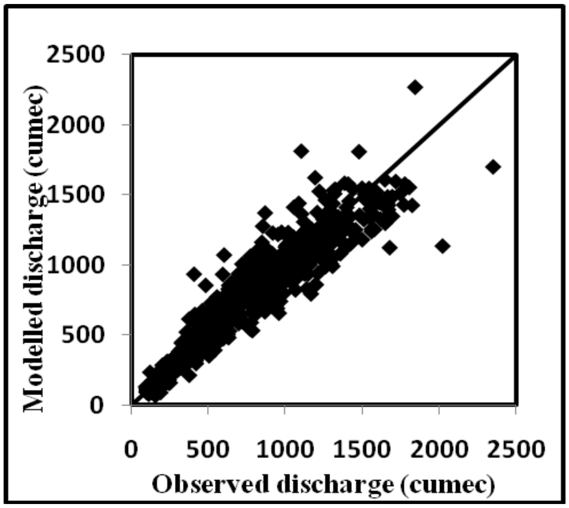

Fig. 31: Validation result of ANN model (1 day lead, *tansigmoidal*)

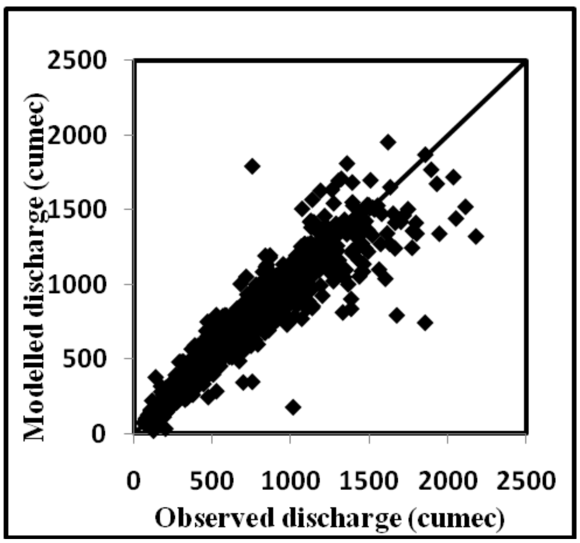

Fig. 32: Testing result of ANN model (1 day lead, *tansigmoidal*)

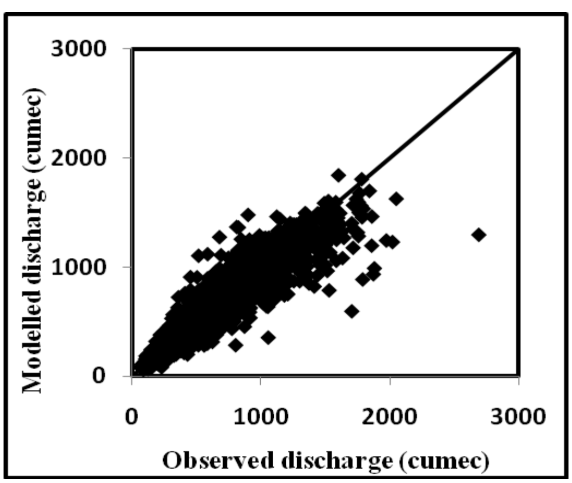

Fig. 33: Calibration result of ANN model (2 day lead, *tansigmoidal*)

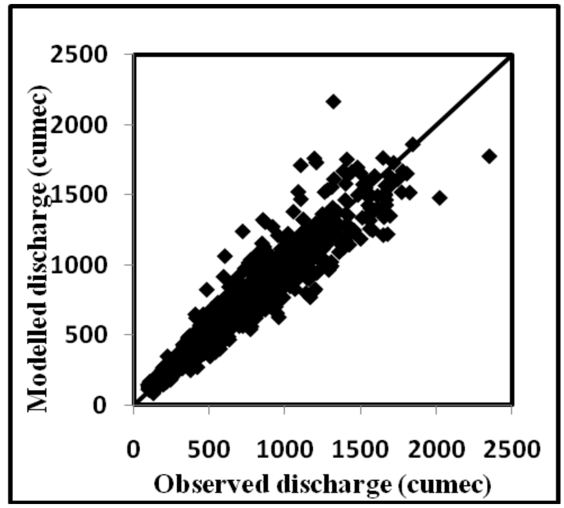

Fig. 34: Validation result of ANN model (2 day lead, *tansigmoidal*)

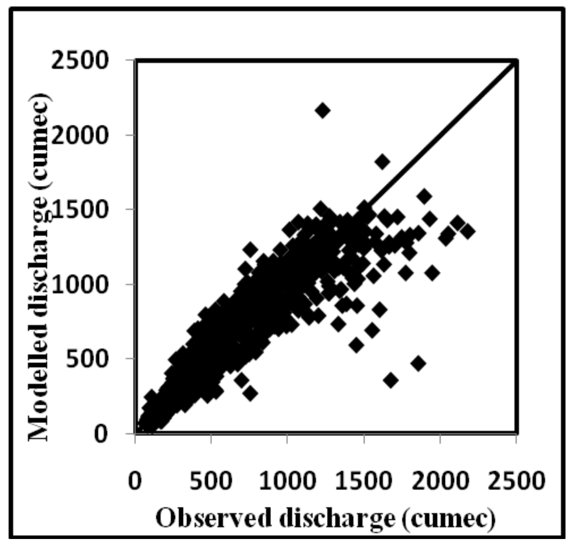

Fig. 35: Testing result of ANN model (2 day lead, *tansigmoidal*)

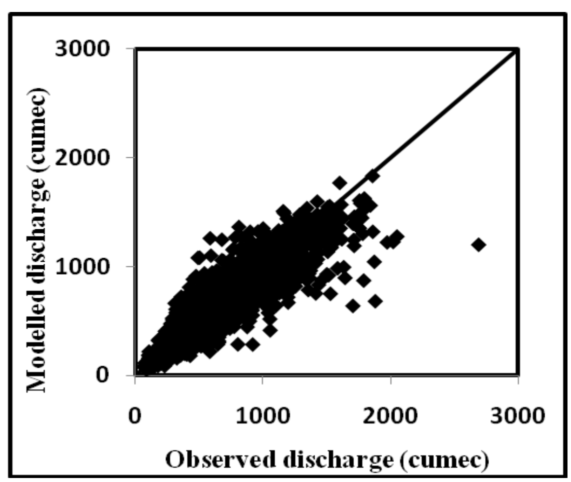

Fig. 36: Calibration result of ANN model (3 day lead, *tansigmoidal*)

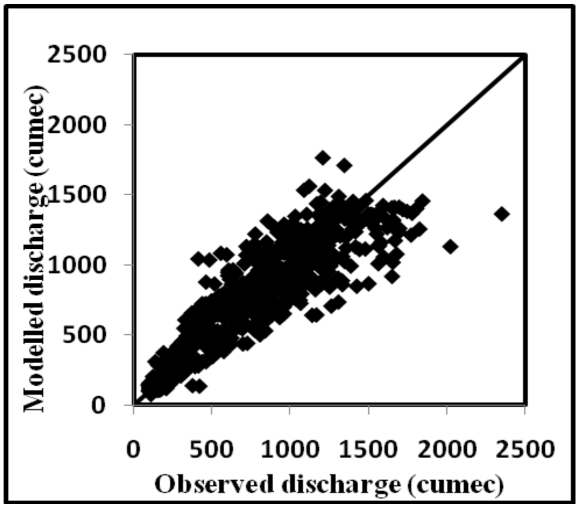

Fig. 37: Validation result of ANN model (3 day lead, *tansigmoidal*)

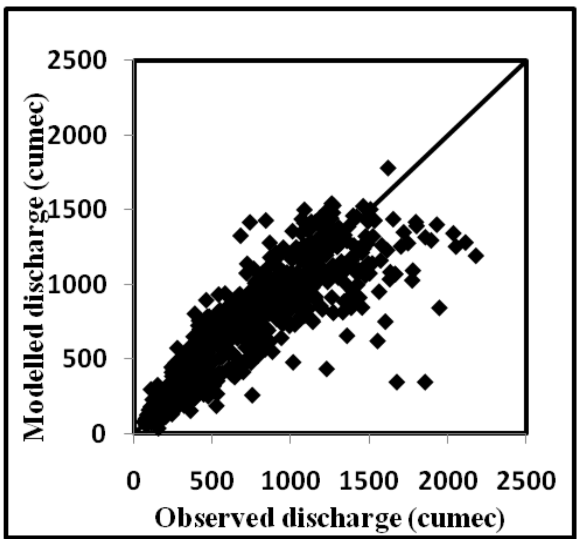

Fig. 38: Testing result of ANN model (3 day lead, *tansigmoidal*)

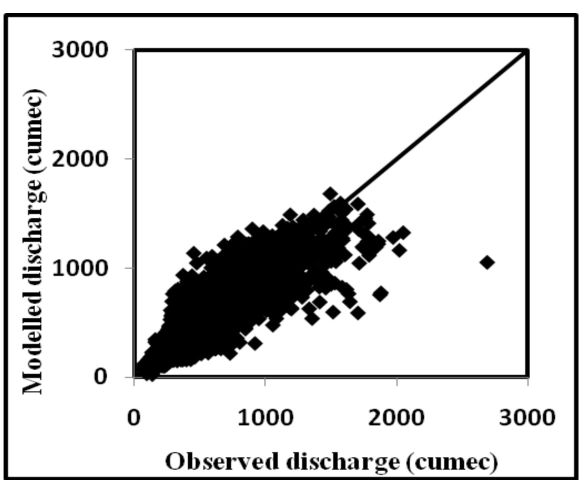

Fig. 39: Calibration result of ANN model (6 day lead, *tansigmoidal*)

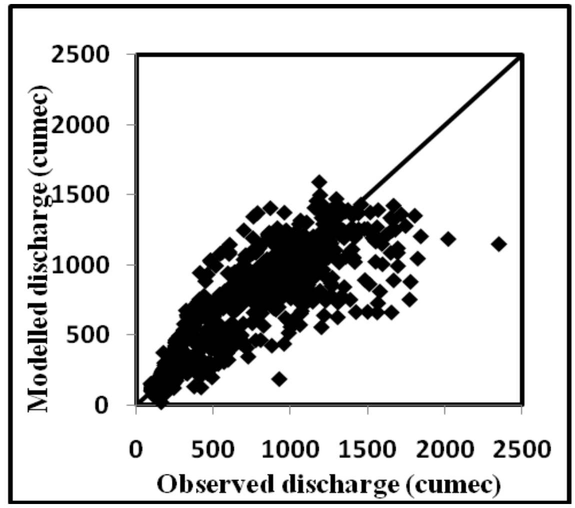

Fig. 40: Validation result of ANN model (6 day lead, *tansigmoidal*)

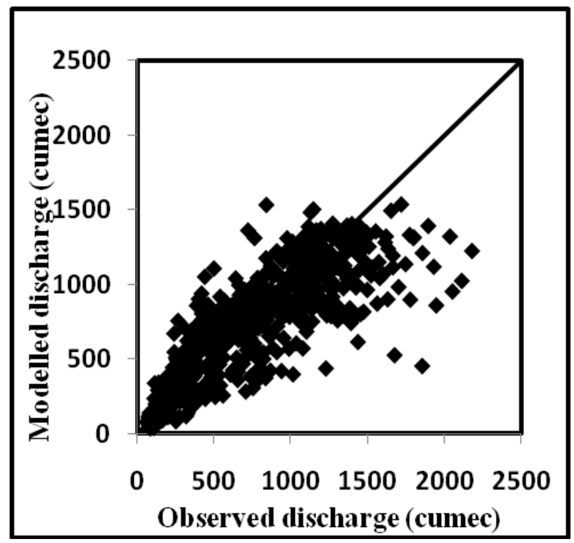

Figure 41 Testing result of ANN model (6 day lead, *tansigmoidal*)

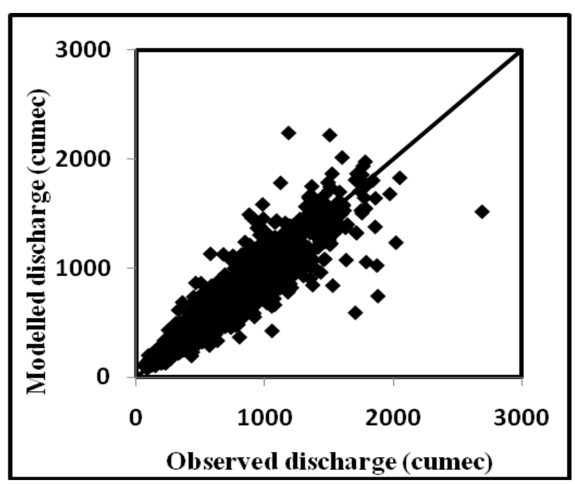

Fig. 42: Calibration result of MLR model (1 day lead)

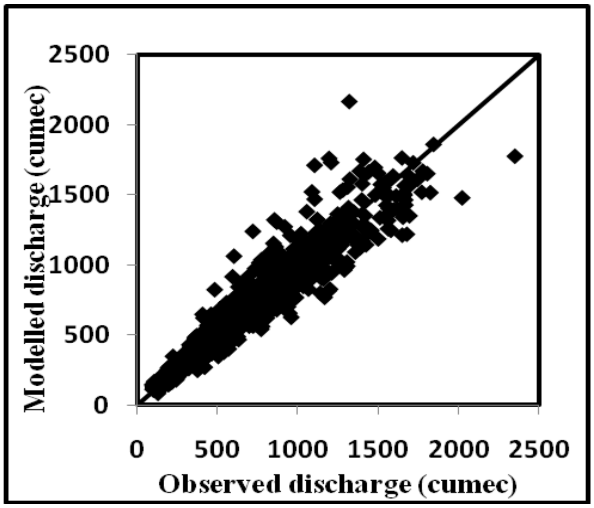

Fig. 43: Validation result of MLR model (1 day lead)

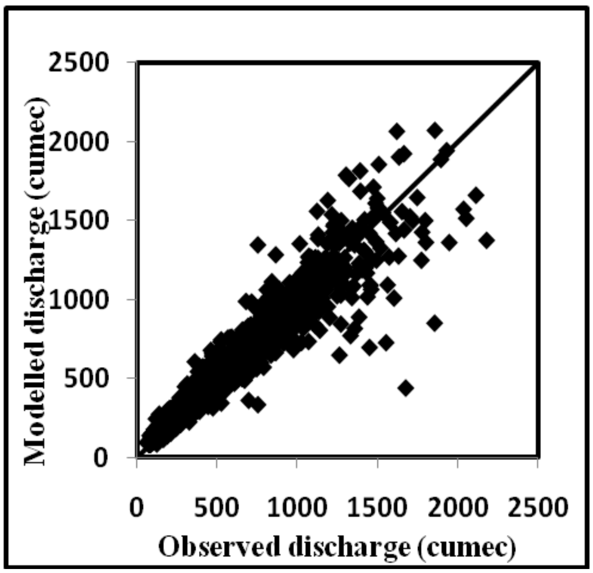

Fig. 44: Testing result of MLR model (1 day lead)

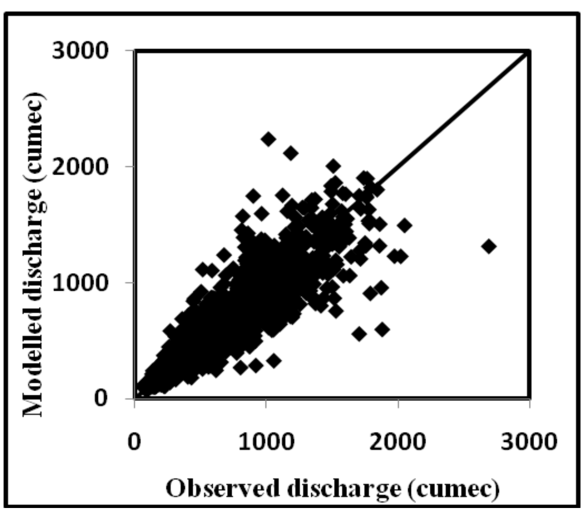

Fig. 45: Calibration result of MLR model (2 day lead)

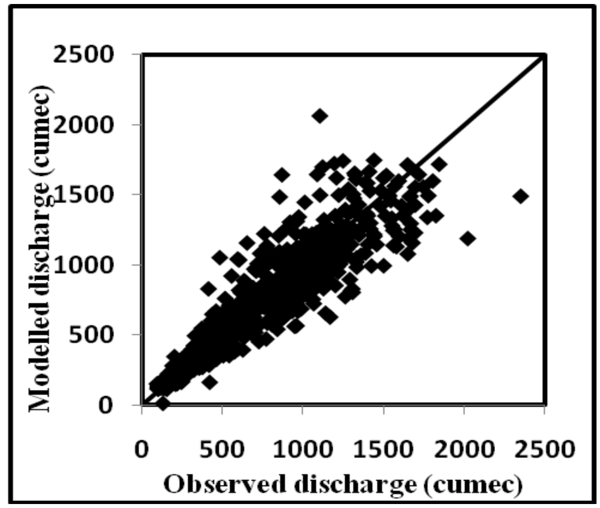

Fig. 46: Validation result of MLR model (2 day lead)

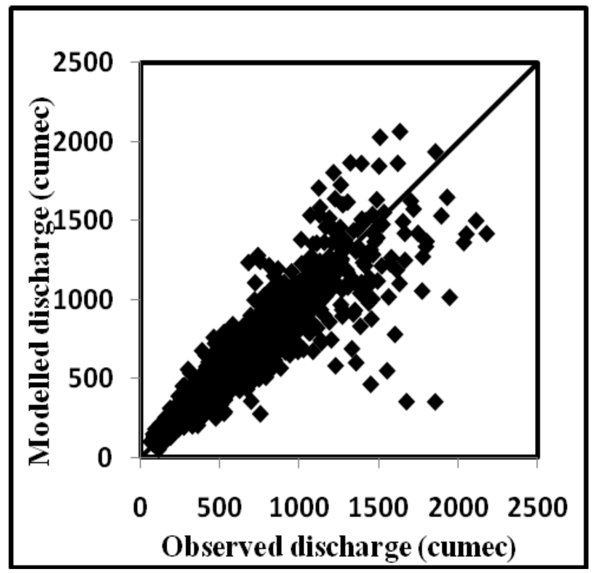

Fig. 47: Testing result of MLR model (2 day lead)

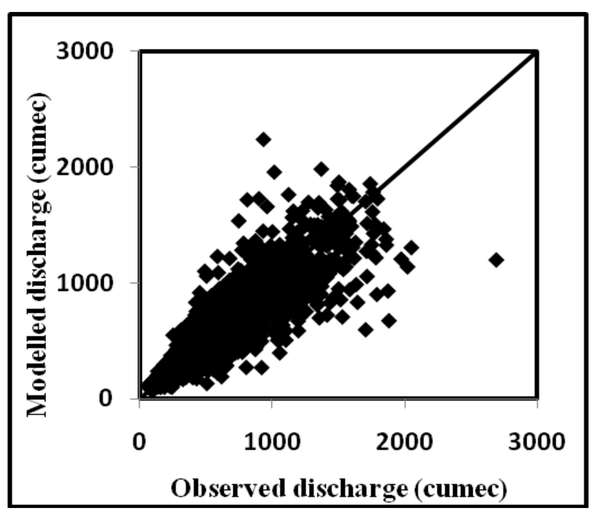

Fig. 48: Calibration result of MLR model (3 day lead)

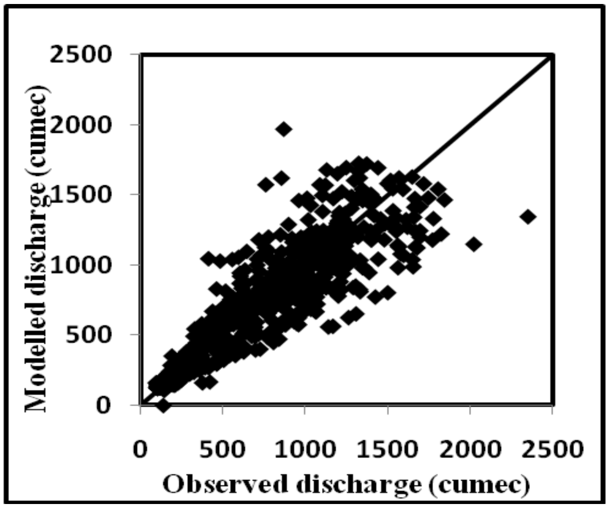

Fig. 49: Validation result of MLR model (3 day lead)

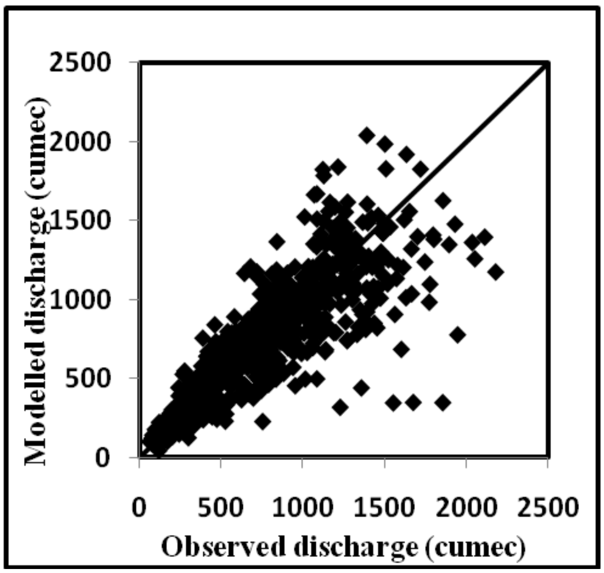

Fig. 50: Testing result of MLR model (3 day lead)

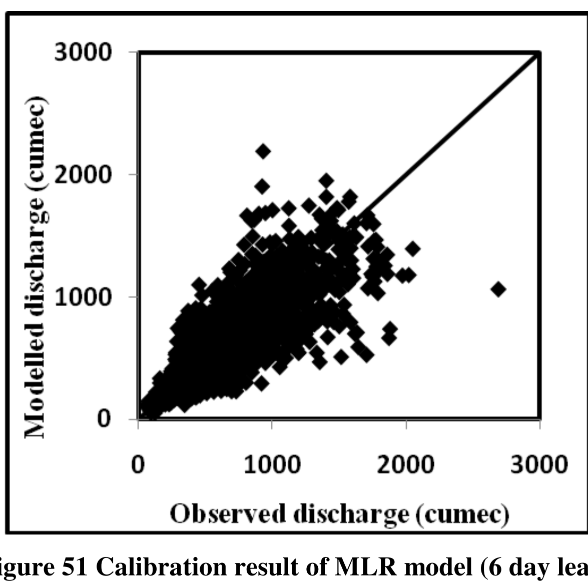

Figure 51 Calibration result of MLR model (6 day lead)

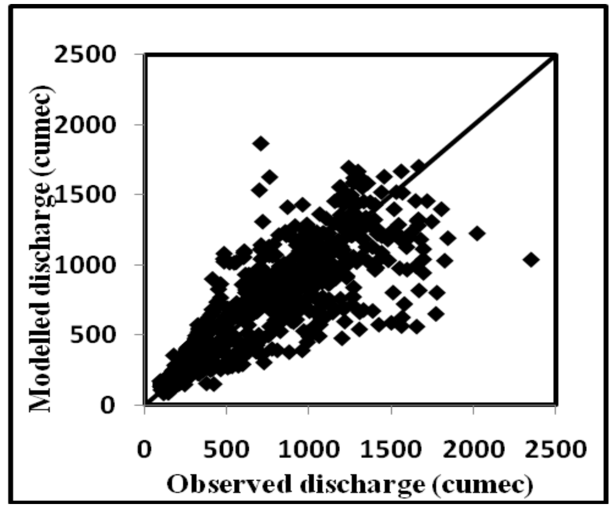

Fig. 52: Validation result of MLR model (6 day lead)

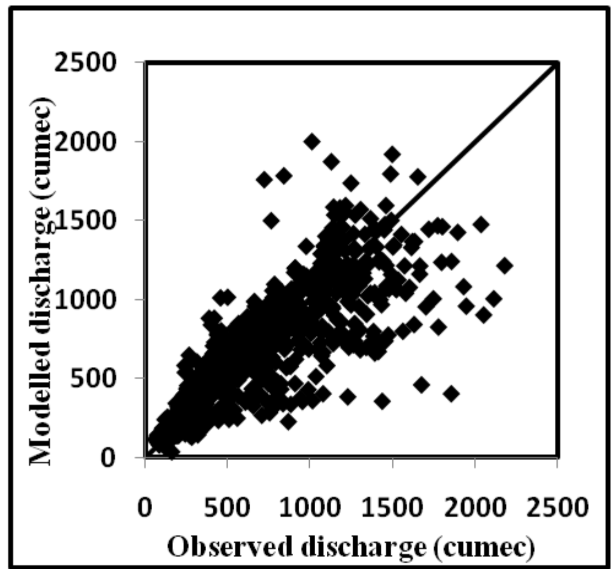

Fig. 53: Testing result of MLR model (6 day lead)

SUMMARY AND CONCLUSION

In this study, an ANN Models have been developed for real time flood forecasting at Kasol gauging site (Bhakra reservoir), Sutlej River Basin. The ANN models have been developed using rainfall values of Kalpa, Rampur, Rackchham, Berthin, Bhakra, Kahu, Kasol, Kasol, Kaza, Namagia and Suni and discharge values of Rampur, Suni and Kasol from 01.09.1984 to 30.04.2005. The lead periods considered for developing the models for forecasting of flood are 1 day, 2 day, 3 day and 6 day. The statistical parameters ACF and PACF of discharge at Kasol and CCF between discharge of Kasol and rainfall values of all the stations and discharge of Rampur and Suni have been used for selection of Input vector for developing the ANN models. The transfer functions, *logsigmoidal* and *tansigmoidal*, have been used for development of ANN models for forecasting the flood values for 1 day, 2 day, 3 day and 6 day lead periods. The comparison of performance indices such as coefficient of correlation, RMSE and model efficiency of ANN models with *logsigmoidal* transfer function with ANN models *tansigmoidal* transfer function suggest that any one of the two transfer functions could be used for the development of ANN models for issuing flood forecasts at Kasol for 1 day, 2 day, 3 day and 6 day lead periods. Comparison of results of ANN models with the results of MLR clearly indicates the better performance ANN models over the MLR models.

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