DROUGHT FORECASTING USING STANDARDIZED PRECIPITATION INDEX

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ABSTRACT *Drought forecasting plays an important role in the planning and management of natural resources including water resource systems of a river basin, since drought has severe effect when it persists over a longer period. Modeling and forecasting of droughts, which are nonlinear and non-stationary, is a complex exercise. During the last decade neural networks have shown great ability in modeling and forecasting nonlinear and non-stationary time series. In this study an application of the back propagation feed forward recursive ANN models are presented to forecast droughts. The models were applied to forecast droughts using standardized precipitation index series as drought indices in the Kansabati River Basin, which lies in the Purulia District of West Bengal. The resulting trained network is capable of forecasting with satisfactory results upto 2-months of lead time. The model can be used for water resource management in the river basin.*

Key words Kansabati River Basin; neural networks; standardized precipitation index; drought indices.

INTRODUCTION

Research has shown that the lack of a precise and objective definition in specific situations has been an obstacle in understanding the drought phenomenon, which has led to indecision and inaction on the part of managers, policy makers, and others. The global climate change in recent years is likely to enhance the incidences of drought. While much of the weather that we experience is brief and short-lived, drought is a more gradual phenomenon, slowly taking hold of an area and tightening its grip with time. In severe cases, drought can last for many years, and can have devastating effects on agriculture and water supplies. It may be difficult to determine when a drought begins or ends. A drought may either be short event lasting just a few months, or it may persist for years before climatic conditions return to normalcy. Because the impacts of a drought accumulate slowly at first, a drought may not even be recognized until it has become well established.

During the period from 1967 to 1992, droughts have affected about 50% of the 2.8 billion people who suffered from all natural disasters. Because of direct and indirect impacts of droughts, 1.3 million lives were lost, out of a total number of 3.5 million people killed by disasters (Obasi, 1994). Nearly 50% of the world's most populated areas are highly vulnerable to drought. More importantly, almost all of the major agricultural lands are located there (USDA, 1994). Drought produces a complex web of impacts that spans many sectors of the economy and reaches well beyond the area experiencing physical drought. Just as in many agricultural regions of the world, in India also drought is quite common. The drought-prone areas of India are mainly confined to the Peninsular and Western parts and there are also few pockets in other parts of India. Out of 795 Mha of geographical area in India, about 260 Mha of land have been subjected to different degrees of water stress and drought conditions.

Drought forecasting plays an important role in the mitigation of impacts of drought on water resources systems. Traditionally, statistical models have been used for hydrologic drought forecasting based on time series analysis. Regression models and autoregressive moving average (ARMA) models are the typical models for statistical analysis of time series for drought forecasting. However they are basically linear models assuming that data are stationary, and have a limited ability to capture non-stationarities and nonlinearities in the data. Univariate Box-Jenkins ARIMA analysis has been extensively used for forecasting hydrologic variables of interest such as, annual and monthly streamflows, precipitation etc. Hydrologists have generally accepted these methods over the past several decades. However, it is necessary for hydrologists to consider alternative models when nonlinearity and nonstationarity plays a significant role in the forecasting. In recent decades, artificial neural networks (ANNs) have shown great ability in modeling and forecasting nonlinear and nonstationary time series in hydrology and water resource engineering due to their innate nonlinear property and flexibility for modeling. Some of the advantages of ANNs are (ASCE, 2000 a, b):

- Ability to recognize the relation between the input and output variables without explicit physical considerations;
- Work well even when the training sets contain noise and measurement errors;
- Ability to adapt to solutions over time to compensate for changing circumstances; and
- Possess other inherent information processing characteristics and once trained are easy to use.

Application of ANNs to solve civil engineering problems began in the late 1980s (Flood and Kartam, 1994a, b). Preliminary concepts of ANNs and their adaptability to hydrology are well documented in ASCE (2000a) and also by Govindraju and Rao (2000). An exhaustive list of references on ANN applications in hydrology is given in ASCE (2000b). ANN application to simulation and forecasting problems in water resources has shown great ability. Some of the ANN applications in hydrology are by Karunanithi et al. (1994) and Hsu et al. (1995), who predicted the flow at the catchment outlet with rainfall, upstream flow, and/or temperature as the only inputs. Likewise, Campolo et al. (1997) applied ANN for river flow forecasting, while Nagesh Kumar et al. (2004) used recurrent neural networks for river flow forecasting.

ARMA models, pattern recognition techniques, physically based models using either Palmer Drought Severity Index (PDSI) or Standardized Precipitation Index (SPI) or moisture adequacy index involving Markov chains or the notion of conditional probability seem to offer a potential to develop reliable and robust forecasting methods (Panu and Sharma, 2002). While Rao and Padmanabhan (1984) investigated the stochastic nature of yearly and monthly Palmer Drought Index (PDI) and therefore used the valid stochastic models to forecast and to simulate PDI series, Sen (1990) predicted the possible critical drought durations that may result from any hydrologic phenomenon during any future period using second order Markov chain. On the other hand, Kim and Valdes (2003) used PDSI as a drought forecasting parameter in the Conchos River basin of Mexico.

The neural network models presented in this paper are based on SPI as the drought index. The SPI is used in this study due to its following advantages, as discussed by Hayes et al. (1999). The main advantage is that SPI is based on rainfall alone, so that drought assessment is possible even if other hydro-meteorological measurements are not available. Secondly, SPI is also not adversely affected by topography. Another advantage of SPI is its variable timescale, which enables it to describe drought conditions important for a range of meteorological, hydrological and agricultural applications. The fourth advantage of SPI comes from its standardization, which ensures that the frequencies of extreme events at any location and on any time scale are consistent. The nature of the SPI allows an analyst to determine the rarity of a drought or an anomalously wet event at a particular time scale for any location in the world that has a precipitation record. Lastly, SPI can also detect moisture deficit more rapidly than PDSI, which has a fairly long response time scale of approximately 8-12 months (Hayes et al., 1999).

The main objective of present paper is to calculate time series of SPI for multiple time scales, and to develop a neural network model in order to better forecast drought than any other linear stochastic models (Mishra and Desai, 2006).

STUDY AREA

The study area considered in this study is the portion of Kansabati River Basin upstream of Kangsabati Dam, in the extreme western part of West Bengal. The region has an area of 4,265 km^2. The major crops grown in the catchment are paddy, maize, pulses and vegetables. This area is considered to be drought prone due to irregular rainfall and mostly lateritic soil condition with low water holding capacity. About 50 to 60% of the study area is upland, which is generally managed by small and poor farmers. Lands are mostly mono-cropped having limited surface irrigation facilities. Irrigated crops are not widespread because of insufficient water. For this study, monthly rainfall data were procured for the period from 1965 to 2001 for five rain gauge stations (Table 1). Thiessen polygon method was used to compute the average rainfall over the basin. The SPI time series was derived for average rainfall over the basin and these SPI were used as drought index for forecasting drought.

Table 1 Raingauge stations considered in the Kansabati River Basin.

Raingauge Stations	Elevation (m) above m.s.l.	Geographic coordinates		Statistical properties of annual rainfall series (1965 to 2001)					
		Latitude	Longitude	Mean (mm)	Max (mm)	Min (mm)	Standard deviation	Skewness	Kurtosis
Simulia	220.97	23° 10'	86° 22'	1300.68	1840	828	260.32	0.174	-0.605
Rangagora	222.92	23° 04'	86° 24'	1152.57	1729	743	219.1	0.782	0.656
Tusuma	158.6	23° 08'	86° 43'	1268.3	1683	746	239.31	-0.221	-0.547
Kharidwar	135.96	23° 00'	86° 38'	1216.97	1814	827	248.2	0.637	-0.306
Phulberia	144.32	22° 55'	86° 37'	1345.7	2081	674	322.73	0.329	-0.006

Development of SPI Time Series in the Kansabati Basin

A deficit of precipitation impacts the soil moisture, streamflow, reservoir storage, and groundwater level, etc. on different time scales. As discussed earlier, SPI is used in this study for its inherent advantages. The evolution of the SPI is briefly described here. McKee et al. (1993) initially developed the SPI to quantify precipitation deficits over multiple scales. Bussay et al. (1999) as well as Szalai and Szinell (2000) assessed the utility of SPI for describing drought in Hungary. They concluded that SPI was suitable for quatifying most types of drought event. Streamflow was best described by SPIs with time scale of 2-6 months. Strong relationships to ground water level were found at time scales of 5-24 months. Agricultural drought (i. e., deficit of soil moisture content) was replicated by the SPI on a scale of 2-3 months. Lana et al. (2001) recently used the SPI to investigate patterns of rainfall over Catalonia in Spain. Hughes and Saunders (2002) studied drought climatology for Europe based on monthly SPIs at time scales of 3, 6, 9, 12, 18, and 24 months for the period from 1901-1999. A drought event occurs at the time when the value of SPI is continuously negative. The event ends when the SPI becomes positive. Table 2 provides a drought classification based on SPI.

Table 2 Drought classification based on SPI.

SPI values	Class
>2	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1 to -1.49	Moderately dry
-1.5 to-1.99	Severely dry
< -2	Extremely dry

Computation of SPI The SPI is computed by fitting a probability density function to the frequency distribution of precipitation summed over the time scale of interest. This is performed separately for each month (or for any other temporal basis of the raw precipitation time series) and for each location in space. Each probability density function is then transformed into a standardized normal distribution.

The gamma distribution is defined by its probability density function as:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \qquad \text{for } x > 0 \tag{1}$$

where α is a shape factor, β is a scale factor and x is the amount of precipitation. All these three parameters always have positive values. $\Gamma(\alpha)$ is the gamma function which is defined as

$$\Gamma(\alpha) = \int_{0}^{\infty} y^{\alpha-1} e^{-y} dy \tag{2}$$

Fitting the distribution to the data requires α and β to be estimated. Edwards and McKee (1997) suggested the estimation of these parameters using the approximation of Thom (1958) for maximum likelihood as follows:

$$\hat{\alpha} = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right) \tag{3}$$

$$\hat{\beta} = \frac{\overline{x}}{\hat{\alpha}} \tag{4}$$

$$A = \ln(\overline{x}) - \frac{\sum \ln(x)}{n} \tag{5}$$

where n is the number of observations.

The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})}\int_0^x x^{\hat{\alpha}-1} e^{-x/\hat{\beta}} dx \tag{6}$$

Substituting t for $x/\hat{\beta}$ reduces equation to incomplete gamma function. McKee et al. (1993) used an analytic method along with suggested software code from Press et al. (1986). Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1\text{-}q)\, G(x) \tag{7}$$

where q is the probability of zero precipitation.

The cumulative probability, $H(x)$, is then transformed into a standard normal random variable Z (i.e., with a zero mean and a unit variance), which is the value of SPI. Following Edwards and McKee (1997), and Hughes and Saunders (2002), we employ the approximate conversion provided by Abramowitz and Stegnum (1965) as an alternative:

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for} \quad 0 < H(x) \le 0.5 \tag{8}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \quad \text{for} \quad 0.5 < H(x) < 1 \tag{9}$$

where

$$t = \sqrt{\ln\left[\frac{1}{(H(x))^2}\right]} \quad \text{for} \quad 0 < H(x) \le 0.5 \tag{10}$$

$$t = \sqrt{\ln\left[\frac{1}{(1-H(x))^2}\right]} \qquad \text{for} \quad 0.5 < H(x) < 1 \tag{11}$$

and

$c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$.

The SPI series for different timescales is shown in Fig. 1. The correlation coefficient between average values of discharge in river and reservoir storage with different SPI series was calculated and shown in Table 3. It is observed that SPI 1 and SPI 3 have significant correlations with Kansabati river flow discharge, and, SPI 3 and SPI 6 have good correlations with the reservoir storage over different months.

Table 3 Correlation matrix of SPI vs hydrological variables.

SPI series	Correlation coefficient with discharge	Correlation coefficient with reservoir storage
SPI 1	0.718	0.317
SPI 3	0.555	0.661
SPI 6	0.359	0.589
SPI 9	0.236	0.224
SPI 12	0.220	0.188
SPI 24	0.099	0.0844

METHODOLOGY

Artificial Neural Networks

Theoretically, it has been shown that given an appropriate number of nonlinear processing units, neural networks can learn from experience and estimate any complex functional relationship with high accuracy. Empirically, numerous successful applications have established their role for pattern recognition and forecasting. Although many types of neural network models have been proposed, the most popular type for time series forecasting is the feed forward neural network model. Figure 2 shows a typical three-layer feed forward model used for forecasting purposes. The input nodes are the previous lagged observations while the output provides the forecast for the future value. Hidden nodes with appropriate nonlinear transfer functions are used to process the information received by the input nodes. In the present paper a recursive multi-step neural network approach is used for forecasting over different lead times.

Recursive multi-step neural network approach (RMSNN) This forecasting technique is similar to ARIMA models in forecasting approach, which has single output node, forecasting a single time step ahead, and the network is applied

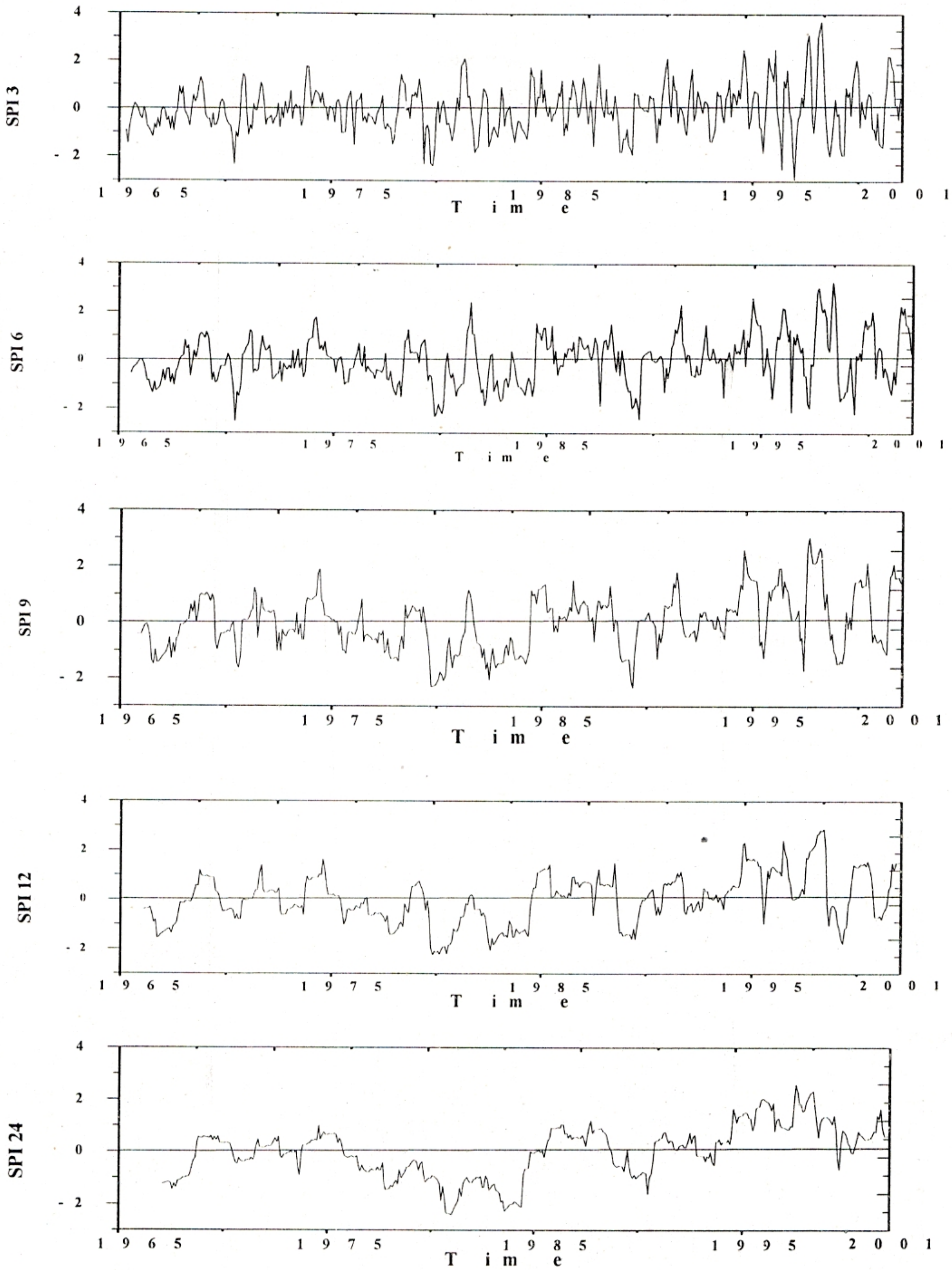


Fig. 1 SPI series over different time scales based on average rainfall over Kansabati Basin.

recursively. These forecast values are again used as input for the subsequent forecasts ahead, as in Figure 2.

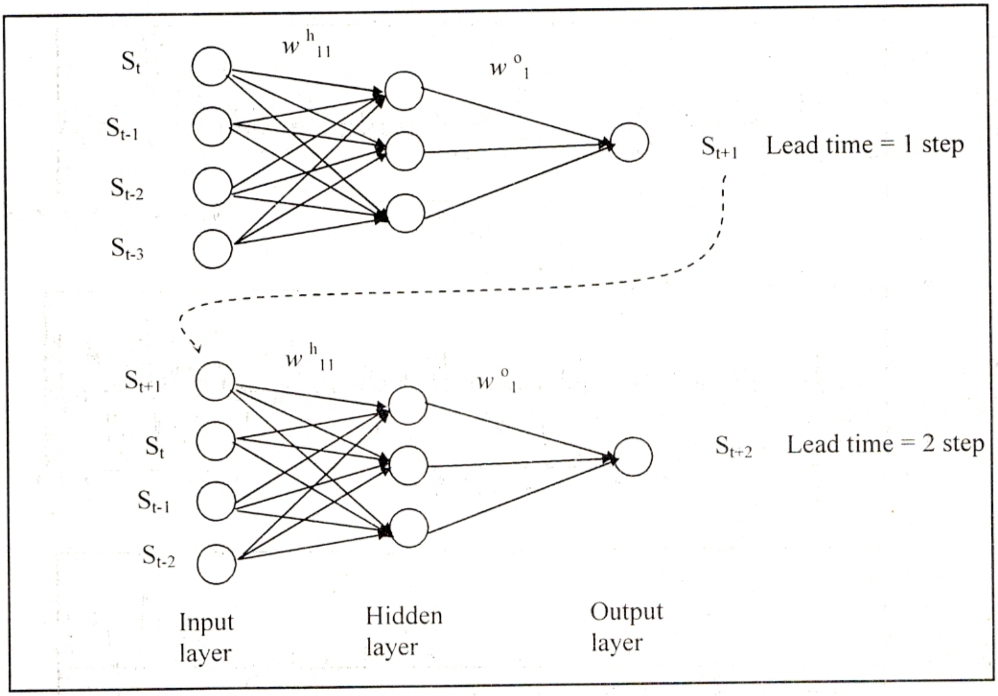


Fig. 2 Feed-forward recursive multi step neural network approach.

To build a model for forecasting, the network is processed through three stages:

1) The training stage where the network is trained to predict future data based on past and present data.
2) The testing stage where the network is tested to stop training or to continue training.
3) The evaluation stage where the network ceases training and is used to forecast future data to calculate different measures of error. Back propagation algorithm, which is essentially a steepest gradient descent method, is used in this study.

Back propagation training algorithm for three layered neural networks Back propagation network (BPN), developed by Rumelhart et al. (1986) is the most prevalent of the supervised learning models of ANN. BPN uses the steepest gradient descent method to correct the weight of the inter-connecting neuron. BPN easily solves the interaction of the processing elements by adding hidden layers. In the learning process, the interconnection weights are adjusted using error convergence technique to obtain a desired output for a given input. In general, the error at the output layer model propagates backwards to the input layer through the hidden layer in the network to obtain the desired output. The gradient descent method is utilized to calculate the weights of the network and to adjust the weights of interconnections to minimize the output error. The error function at the output neuron is defined as

$$E = \frac{1}{2}\sum_{k}(T_k - A_K)^2 \qquad (12)$$

where T_k and A_k represent the actual and predicted values for the output neuron *k*.

The gradient descent algorithm adapts the weights according to the gradient error, which is given by

$$\nabla W_{ij} = -\eta \times \frac{\partial E}{\partial W_{ij}} \tag{13}$$

where η is the learning rate and the general form of $\partial E / \partial W_{ij}$ is expressed as (Rumelhart et al, 1986):

$$\frac{\partial E}{\partial W_{ij}} = -\delta_j^n \; A_i^{n-1} \tag{14}$$

Substituting (14) into (13), the gradient error is

$$\nabla W_{ij} = \eta \, \delta_j^n \; A_i^{n-1} \tag{15}$$

where A_i^{n-1} is the output value of sub-layer related to the connecting weight W_{ij}; and δ_j^n is the error signal, which is computed based on whether or not neuron *j* is in the output layer. If neuron *j* is one of the output neurons, then

$$\delta_j = (T_j - Y_j) Y_j \, (1 - Y_j) \tag{16}$$

If neuron *j* is a neuron of the hidden layer

$$\delta_j = \left[\sum_j \delta_j \left(W_{hy} \right)_{hj} \right] H_h \left(1 - H_h \right) \tag{17}$$

where H_h is the value of hidden layer.

Finally, the value of weight of the inter-connective neuron can be expressed as

$$W_{ij}^m = W_{ij}^{m-1} + \nabla W_{ij}^m = W_{ij}^{m-1} + \eta \, \delta_j^n \; A_i^{n-1} \tag{18}$$

To accelerate the convergence of the error in learning procedure, Jacobs (1988) proposed the momentum term with momentum gain α with its value ranging from 0 to 1, in Eq. (18).

$$W_{ij}^m = W_{ij}^{m-1} + \eta \, \delta_j^n \; A_i^{n-1} + \alpha \, \nabla W_{ij}^{m-1} \tag{19}$$

Design of Network

The use of an ANN for forecasting time series implies that the input nodes reconnected to a number of past-observed values to identify the processes at future time steps. For forecasting several time steps ahead a recursive multi-step method is used. In a recursive multi-step approach based on one output node, forecasting is done for a single step ahead and the network is applied recursively using the previous predictions as inputs for the subsequent forecasts (Fig. 2). The activation function determines the relationship between inputs and outputs of a node in a network. Here, a sigmoid function $\left[1/\left(1+e^{-x}\right)\right]$ is used, which is the most popular choice. Datasets are normalized before the training begins using the equation:

$$X_n = \frac{X_0 - X_{\min}}{X_{\max} - X_{\min}} \tag{20}$$

where X_n and X_0 represent the normalized and original data respectively while $X_{\min}$ and $X_{\max}$ represent the minimum and maximum value among original data.

In time series problems the number of input nodes corresponds to the number of lagged observations used to discover the underlying pattern in a time series and to make forecasts for future values. The hidden layer and its nodes play a very important role in successful application of neural networks. It is the nodes in the hidden layer that allow neural networks to detect the feature, to capture the pattern in the data, and to perform complicated nonlinear mapping between input and output variables. It has been proved that only one layer of hidden units is sufficient for ANNs to approximate any complex nonlinear function with any desired accuracy (Cybenko, 1989; Hornik et al., 1989). The hidden nodes also allow taking into account the presence of non-stationary parameters in the data such as trends and seasonal variations (Maier and Dandy, 1996). In the case of the popular one hidden layer networks, several practical guidelines exist. These include using '$2n+1$' (Lippmann, 1987; Hecht-Nielsen, 1990), '$2n$' (Wong, 1991), 'n' (Tang and Fishwick, 1993), where n is the number of input nodes. Fewer neurons in the hidden layer than in the input layer has worked well in the past (Fletcher and Goss, 1993; Zhang and Dong, 2001). In order to determine the optimal network architecture, the number of neurons in the input and hidden layer were determined by experimentation. Tang and Fishwick (1993) claim that the number of input nodes is simply the number of autoregressive (AR) terms in the Box-Jenkins model for a univariate time series. This is not true because (1) for moving average (MA) processes, there are no AR terms, and (2) Box-Jenkins models are linear models.

The number of AR terms only give the number of linearly correlated lagged observations and it is not appropriate for the nonlinear relationships modeled by neural networks (Zhang et al., 1998). In the present study, the number of input neurons (m) ranged from 1 to 20. For each input layer dimension, the number of hidden layer nodes (n) was progressively increased from 1 to $2n+1$, where n is the corresponding input neurons. The coefficient of correlation for each combination of input and hidden neurons was calculated. The combination having maximum coefficient of correlation was chosen as optimal network. The network was trained for 5,000 epochs using back propagation algorithm with learning rate of 0.01 and momentum coefficient of 0.9.

The performance of the predictions resulting from the neural network models is evaluated by the following measure for goodness-of-fit:

$$\text{Root mean square error} = \text{RMSE} = \sqrt{\frac{1}{p}\sum_{i=1}^{p}\left[(X_m)_i - (X_s)_i\right]^2} \tag{21}$$

$$\text{Mean absolute error} = \text{MAE} = \frac{1}{p}\sum_{i=1}^{p}\left|(X_m)_i - (X_s)_i\right| \quad (22)$$

where the subscripts m and s represent the measured and simulated SPI values, respectively and p is the total number of events considered.

RESULTS AND DISCUSSION

The neural network models are developed to forecast drought in this study using recursive multi-step approach. The available data is split into two parts. The dataset from 1965-1994 is used to estimate the model parameters and the data from 1995-2001 is used to check the forecast accuracy. For SPI 24 the data from 1965-1989 is used to estimate model parameters and the data from 1990-2001 is used to check the forecast accuracy. The data set is different for SPI 24, so as to include more drought incidences, as drought incidences for this time scale are rare. Input data differs for different SPI series, which was found based on experimentation. The coefficient of correlation for each combination taking different input and hidden neurons between observed and simulated data is calculated. The input nodes (m) were varied from 1 to 20 and the corresponding hidden nodes varied from 1 to $2m$+1. The combination having maximum coefficient of correlation is chosen as optimal network. Coefficient of correlation with different combination of input neurons and hidden neurons for SPI 12 is shown in Fig. 3.

In a similar way the optimal architecture for other SPI series are calculated as shown in Table 4. The model performance parameters viz., correlation coefficient (r), root mean square error (RMSE), mean absolute error (MAE) over different lead-time for all SPI series shown in Table 4. The SPI 3, SPI 6, SPI 9, SPI 12 and SPI 24 were forecast over different lead times (1, 2, 3, 4, 5 and 6 months) using optimal networks.

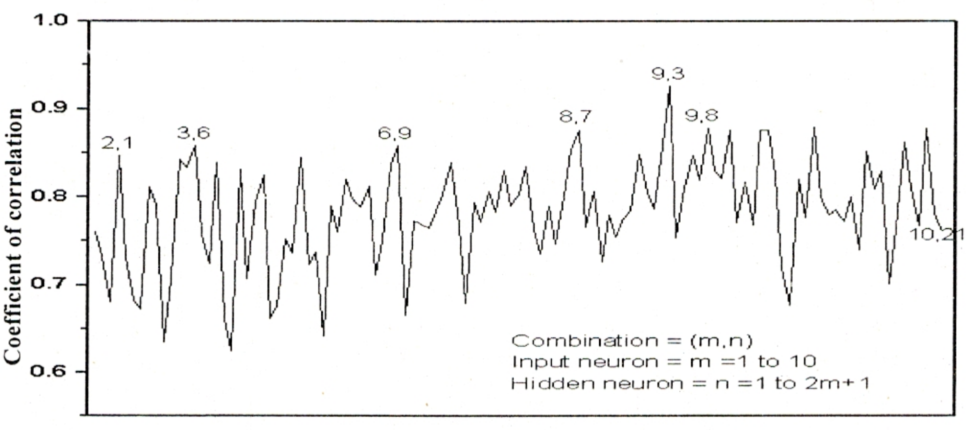


Fig. 3 Correlation coefficient for different combinations of neurons for SPI 12.

Table 4 Comparison of forecasting measures between observed and predicted data for different lead time.

SPI series	ANN Architecture	Forecasting Measures	1 month lead time	2 month lead time	3 month lead time	4 month lead time	5 month lead time	6 month lead time
SPI 3	6-9-1	*r*	0.83	0.67	0.462	0.352	0.302	0.232
		MAE	0.6417	0.8965	1.0724	1.18	1.4025	1.5537
		RMSE	0.8382	1.1567	1.383	1.4325	1.4465	1.4691
SPI 6	7-4-1	*r*	0.8509	0.6307	0.483	0.36	0.295	0.254
		MAE	0.5054	0.8806	1.1185	1.2888	1.4324	1.5346
		RMSE	0.7139	0.9685	1.0994	1.1468	1.2649	1.3749
SPI 9	9-3-1	*r*	0.905	0.766	0.606	0.52	0.462	0.398
		MAE	0.3759	0.6036	0.7843	0.9106	0.9851	1.0825
		RMSE	0.5262	0.7656	0.9092	0.972	1.08	1.0926
SPI 12	9-3-1	*r*	0.93	0.84	0.742	0.68	0.572	0.491
		MAE	0.2831	0.5608	0.7947	0.9372	1.0313	1.0972
		RMSE	0.4101	0.6244	0.7734	0.828	0.9152	1.0075
SPI 24	7-4-1	*r*	0.921	0.801	0.721	0.658	0.622	0.591
		MAE	0.2403	0.4172	0.5374	0.6561	0.7582	0.8615
		RMSE	0.3176	0.4645	0.5397	0.6085	0.6264	0.6423

It is observed that the number of input neurons increases in direct multi-step approach for forecasts with six months of lead time in comparison to recursive approach. The number of hidden layer neurons were also varied corresponding to each input neuron and it is observed that performance of ANN architecture increases when the number of hidden layer neurons is approximately half the number of input neurons. The time series of the observed and one month ahead simulated values for all SPI series are shown in Fig. 4 and the time series of the observed and two to six month lead time forecast values for SPI 12 are shown in Fig. 5. It is observed that with longer lead-time the forecast accuracy decreases between observed and predicted values of SPI.

CONCLUSIONS

The application of ANN has been successfully demonstrated for drought forecasting using SPI in Kansabati River Basin, West Bengal. The objectives of the study have been twofold: firstly to compute the SPI time series to quantify drought over multiple durations in the basin based on the average rainfall. It is observed that SPI 1 and SPI 3 have good correlations with river flow discharge, and, SPI 3 and

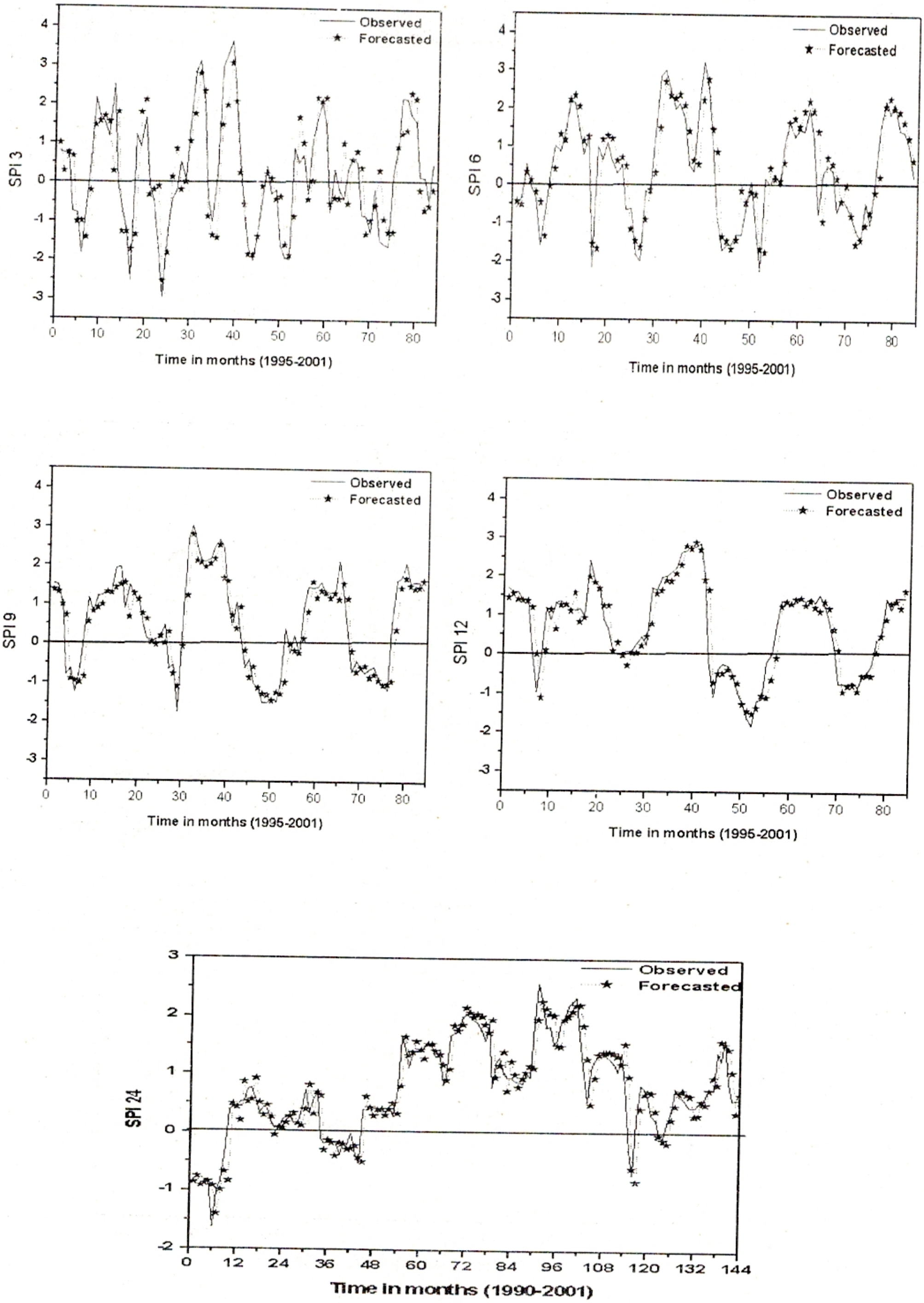
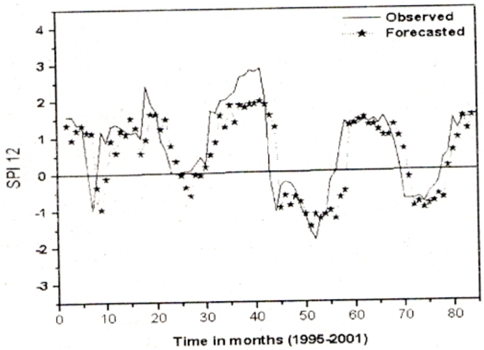
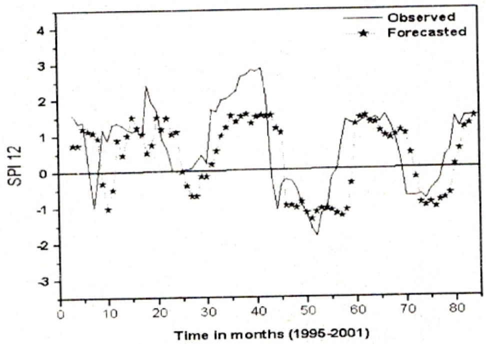


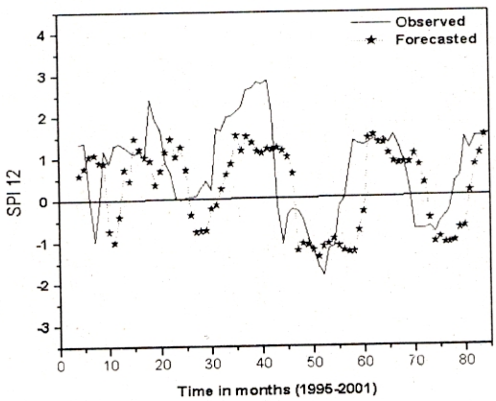
Fig. 4 Comparison of observed data with predicted data over one month lead time using feed-forward recursive neural network for SPI series.



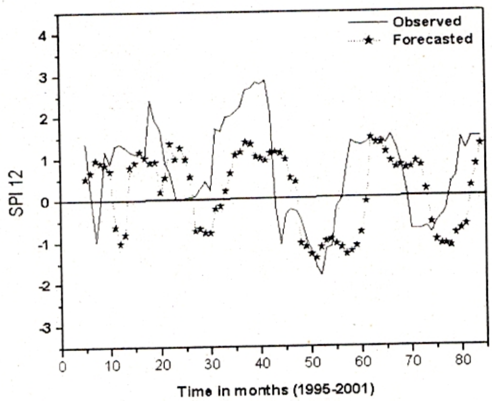
(a) 2 month lead time



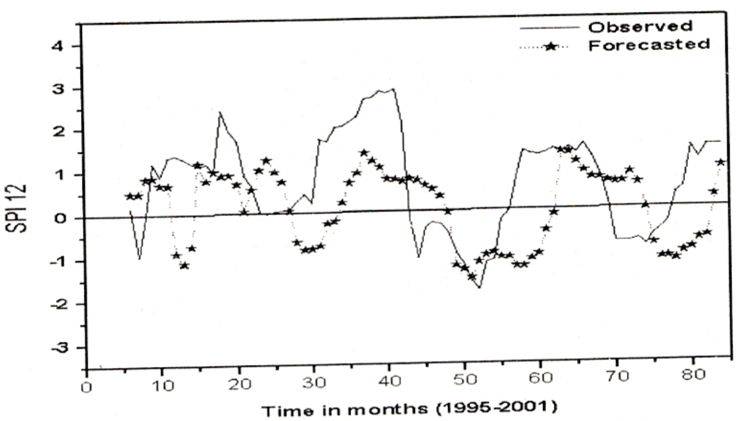
(b) 3 month lead time



(c) 4 month lead time



(d) 5 month lead time



(e) 6 month lead time

Fig. 5 Comparison of observed data with predicted data over different lead time for SPI 12 using feed-forward recursive neural network.

SPI 6 with the storage in the reservoir over different months. The second objective has been to develop ANN models to forecast SPI. The results obtained from the models show that recursive multi-step approach is best suited for prediction with 1-2 months of lead time. These neural network models can be very useful for water resource planners to take necessary precautions in advance considering the severity of drought ascertained by computation of SPI.

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