LONG-TERM FLOOD FORECASTING MODEL FOR THE BRAHMAPUTRA-JAMUNA RIVER USING EL NINO-SOUTHERN OSCILLATION (ENSO)

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ABSTRACT

The El Nino-Southern Oscillation (ENSO) is a dominant pattern of climate variation and thus endures appreciable importance in climate studies. Brahmaputra-Jamuna being one of the largest rivers of the world, having very high variation in flow with seasons, is imposing great difficulty to water management of Bangladesh. This research explores the nature and strength of possible teleconnections between the river flow of Brahmaputra-Jamuna and ENSO variability over the equatorial Pacific Ocean. Hence using the ENSO information efforts have been put to develop a flood forecast model which can capture, at least in part, the natural variability of flows with a reasonable lead-time so that there can be adequate time to plan water management of the region.

This research demonstrates a noteworthy relationship between natural variability of average flood flows of July-August-September (JAS) months of the Brahmaputra-Jamuna River and the ENSO index of the corresponding months. Here sea surface temperature (SST) of the equatorial Pacific Ocean has been used as ENSO index. Frequency distribution shows that during El Nino years (warm ENSO) the probability of exceeding the average JAS flow is only around 25% while during La Nina years (cold ENSO) this probability rises to about 77%. Correlation analysis explains that the JAS SST of Nino 4 region has significant influence on the average JAS flow of Brahmaputra-Jamuna. Discriminant analysis (high-flood with La Nina and low-flood with El Nino) has been performed to evaluate the possibility of long-lead forecasting. Several ocean-atmosphere coupled models are available nowadays which can predict SST with a lead-time more than one year. So if SST can be predicted accurately, sufficiently long-time before the flood event, the probability of high, average or low floods can be forecasted for the corresponding lead-time.

Subsequently a flood forecasting statistical model has been developed for the Brahmaputra-Jamuna using historical flows (1977-1999) and predicted SSTs and its gradients. Verification of the model, for the years 2000-2004, shows an error of less than 15% at 3-months lead-time. However, the forecast skill of the model is dependent on the accuracy of SST prediction.

1. INTRODUCTION

Bangladesh is a riverine country. Seasonal river runoff in this country is extremely variable, imposing appreciable difficulties in water management activities. Floods of Brahmaputra-Jamuna are of major natural hazards capable of producing disaster of national significance. Growth in population and extensive encroachment of floodplains in the recent years have increased the flood risk and made the country more exposed to huge losses during large floods. Over the years large investments have been made to build physical infrastructure for flood protection, but it has been proved that it is not realistic both economically and

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technically to implement solely such mitigation approach. The choice of non-structural measure is so far focused mainly on flood forecasting, because many of the other measures including floodplain zoning, compulsory acquisition of flood prone land, relocation, etc have proved unsuitable for Bangladesh (Bari and Hassan, 2005).

In Bangladesh 75 to 80 percent of annual rainfall occurs during June/July to September/October and most of it occurs during 25 to 60 rainy days. Deficiency of adequate and authentic data from upper riparian countries hampers flood forecasting in Bangladesh. Moreover hydrologic forecasts of the basin through rainfall-runoff modeling could provide a lead-time on the order of the basin response time, which are several days or so. Such a short forecasting lead-time is not adequate to plan for extreme events (floods). To facilitate basin wide planning and management of water resources, it is desirable to capture river discharge variability with a forecasting lead-time of a few months to a year. Therefore considering the importance of flood forecasting and limited scope of rainfall-runoff modeling, it has become essential for Bangladesh to develop an alternative flow forecasting method using information like El Nino-Southern Oscillation (ENSO).

Large-scale coupled ocean-atmosphere oscillation in the Pacific Ocean, known as ENSO, is related to inter-annual variation in precipitation and stream flow in several regions of the world. The term El Nino refers to the large-scale ocean-atmosphere climate incident linked to a periodic warming in sea-surface temperature across the central and east-central equatorial Pacific. El Nino represents the warm phase of the ENSO cycle. Oppositely the cold phase is known as La Nina. There have been several attempts made to make quantitative definitions of El Nino (Trenberth, 1997). NOAA's Climate Prediction Center, which is part of the US National Weather Service, declares the onset of an El Nino episode when the 3-months average sea surface temperature departure exceeds 0.5ºC in the east-central equatorial Pacific. It is also recognized that the ENSO temperature signal pervades the entire tropical belt. Ropelewski and Halpert (1996) have identified 19 regions throughout the world whose precipitation characteristics are related to the ENSO phenomena. Indian Subcontinent is one of those 19 regions. Studies by several researchers (Rasmusson and Carpenter, 1983; Shukla and Paolino, 1983; Parthosarathy and Pant, 1985; Kiladis and Sinha, 1991) also explored the possible relationships between ENSO and precipitation in Indian Subcontinent. A study by Whitaker et al. (2001) showed that Ganges River flood is correlated with ENSO La Nina event. Eltahir (1996) used ENSO as a predictor of natural variability of flow in the Nile River; Simpson et al. (1993) related the Murray-Darling River discharge of Australia with ENSO. Recent studies indicate that ENSO events can be predicted one to two years in advance using coupled ocean-atmosphere models, such as, Coupled General Circulation Model, Statistical Model (Canonical correlation), Linear Inverse Model, etc. Therefore the ability to predict flow pattern in rivers will be highly enhanced if a strong relationship between river discharge and ENSO exists, and is quantified. Hence using this relationship a statistical approach for flood forecasting of river has been developed. This model will provide sufficient lead-time for flood preparedness and as such seasonal forecasts will be invaluable to the management of land and water resources of a country.

2. DATA

Discharge data of Brahmaputra-Jamuna River at Bahadurabad Station (1977- 2004) has been collected from Bangladesh Water Development Board (BWDB). In this research sea surface temperature (SST) of Nino 4 [between 5°N-5°S and 160°E-150°W] and Nino 3.4 [between 5ºN-5ºS and 170ºW-120ºW] regions of equatorial Pacific Ocean has been used as ENSO index to identify the ENSO signal. The actual SST data has been collected from

National Centre for Environmental Prediction (NCEP) of National Oceanic and Atmospheric Administration (NOAA). The SST predicted data of Linear Inverse Model has been collected from NOAA-CIRES/Climate Diagnostic Centre, Colorado.

3. METHODOLOGY

To explore the possible correlation between river flow and ENSO, cumulative frequency distribution of standardized river flow data have been used. The data series are standardized by subtracting the mean value and dividing by standard deviation. Monthly and contemporaneous average river flows are used in regression analysis to evaluate the relationship with ENSO of the Nino 4 and 3.4 regions. Then discriminant prediction approach, also known as ‘categoric prediction’ has been used for the assessment of long-range flood probabilities. This approach forecasts the categoric probabilities of the predictand (river flow) according to the categories that the predictors (SST) fall into. In order to judge the forecasting skill and to compare different forecasts, a synoptic parameter, the Forecasting Index (FI) has been used. Attempt has been made to develop a forecasting model which will forecast efficiently and capture the size of the flow. As such, using order-one autoregressive model AR(1), and the teleconnection between ENSO and river flow, a statistical model has been developed which will capture the wet-season flow of the river Brahmaputra-Jamuna.

4. IDENTIFICATION OF TELECONNECTION BETWEEN ENSO AND BRAHMAPUTRA-JAMUNA RIVER FLOW

Frequency distribution of the river flow with ENSO

The Brahmaputra-Jamuna River has a distinct wet-season flow. The monthly averages are shown in Figure 1, which indicates that most of the peak flows occur between July and September. For this reason average flow of these three months, July-August-September (JAS) has been used for identifying the teleconnection of ENSO with flood flows.

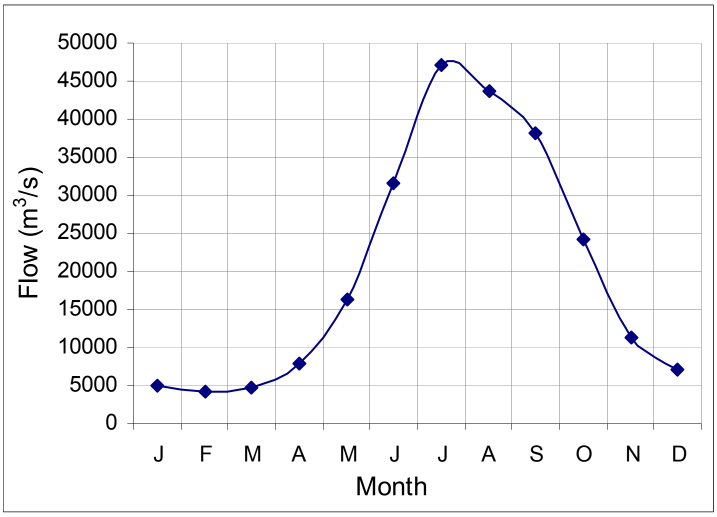

Figure 1. Monthly average flows of Brahmaputra-Jamuna River

To identify the possible teleconnection between ENSO and Brahmaputra-Jamuna River flows, cumulative frequency distribution of standardized annual flows are plotted in Figure 2 which shows that for the full time series, for example, in a given year, the probability of exceeding the long-term average annual flow is 40%. For the standardized time series the average corresponds to zero. During the El Nino year, this probability drops to approximately 22% while for La Nina years the probability rises to around 60%. This shows the clear influence of ENSO events on the annual flows of Brahmaputra-Jamuna.

On the other hand, the cumulative frequency distribution of average JAS flows of Brahmaputra-Jamuna in Figure 3 also supports the influence of ENSO. From the frequency distribution of JAS flows it has also been found that during El Nino years the probability of exceeding the long-term average JAS flow is only around 25% while during La Nina years this probability rises to about 77%.

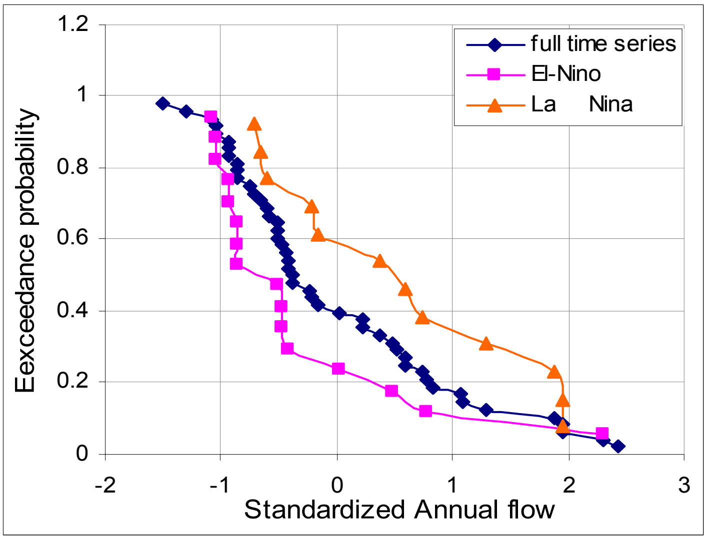

Figure 2. Cumulative frequency distributions of the standardized annual flows in Brahmaputra-Jamuna River for full time series, El Nino and La Nina years

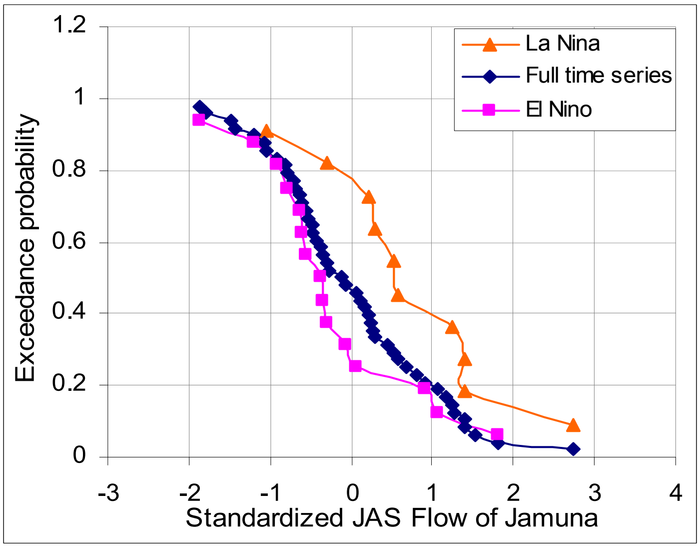

Figure 3. Cumulative frequency distributions of standardized JAS flows in Brahmaputra-Jamuna River for full time series, El Nino and La Nina years

Correlation analysis between river flow and SSTs of Nino regions

Both ENSO index and flow are averaged over different months and time-periods of the year. Correlation analysis has been performed to measure the influence of different months and time periods SSTs' of Nino 4 and 3.4 regions on the flood flows of Brahmaputra-Jamuna River. The analyses show the JAS SST of Nino 4 has more significant influence on the flood flows of Brahmaputra-Jamuna (see Table 1) and hence has been chosen for further analysis.

Table 1. Correlation between average JAS flow of Brahmaputra-Jamuna and SSTs of different time-periods (of Nino 4 and 3.4) of the corresponding years

Region	Independent variable	Coefficient of regression, R	Coefficient of determination, R^2	F-statistic	p-statistic
Nino 4	May-June-July (MJJ) SST	−0.328	0.107	3.01	0.095
	June-July-August (JJA) SST	−0.444	0.197	6.13	0.035
	July-August-September (JAS) SST	−0.494	0.244	8.06	0.015
Nino 3.4	May-June-July (MJJ) SST	0.323	0.105	2.80	0.107
	June-July-August (JJA) SST	0.415	0.172	4.99	0.035
	July-August-September (JAS) SST	0.405	0.164	4.72	0.040

5. DISCRIMINANT ANALYSIS

Probability of flow for given ENSO index

The discriminant prediction approach, also known as ‘categoric prediction’ will be used here for the assessment of long-lead flood possibilities. This approach will forecast the categoric probabilities of the predictand (river flow) according to the categories that the predictors (SST) fall into. Using the strong correlation between the JAS flow in the Brahmaputra-Jamuna and the JAS ENSO index, a conditional probability table is prepared to forecast the JAS flow. Both of the series are standardized by deducting the mean value and dividing by the standard deviation. The flow is categorized into high, average and low by using plus and minus half standard deviation from the mean. On the other hand SST is categorized into warm, normal and cold by using plus and minus one standard deviation from the mean.

Any categoric probability can be computed by counting all the relevant data points, and normalizing it by the number of all data points that satisfy the condition. Here the main interest is on the conditional categoric probabilities. All the data points which fulfill the given condition (suppose cold, normal or warm) are counted; then those cases with a low, average and high flows are identified, and the relative frequency distribution are obtained. Then the forecasting probability of each flow category can be computed. Considering all possible combinations of ENSO and river flow, the total data points have been divided into nine groups.

Figure 4 and Table 2 show the conditional probabilities of JAS flows using ENSO as predictor based on the observations from 1977-2004. The table reveals that the addition of ENSO information modifies the forecasting probability of flow to a large extent. With the additional knowledge of a warm event (El Nino year), the probability of high-flow drops to 0.25 and low-flow rises to 0.63. For the same observations it has been found that during a cold event (La Nina year) the probability of high-flow rises to 1.0 and probability of low flow drops to 0.

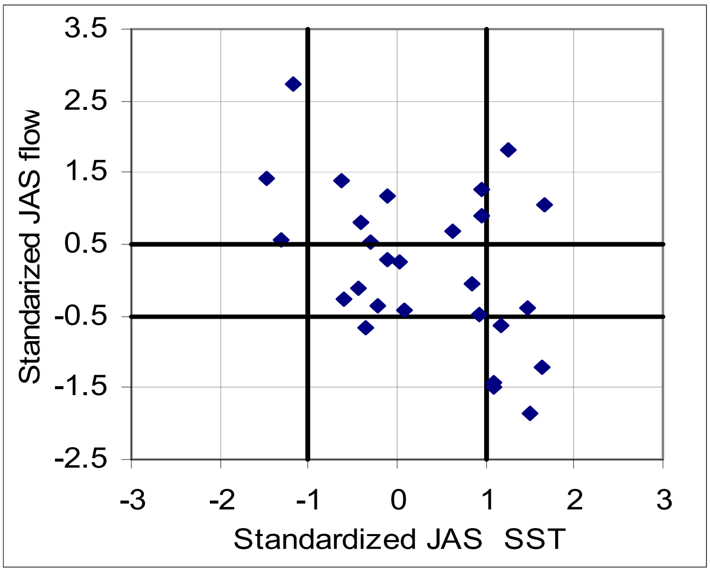

Figure 4. Categories of JAS flow of Brahmaputra-Jamuna and JAS SST of Nino 4 (1977-2004); all combination of SST and corresponding flow are shown through 9 sub-groups

Table 2. Conditional probability of the JAS flow of Brahmaputra-Jamuna, given the JAS ENSO index of Nino 4 region (JAS SST) and based on observation of 1977-2004

JAS ENSO condition	JAS flow		
	Low	Average	High
Cold	0.0	0.0	1.0
Normal	0.06	0.56	0.38
Warm	0.63	0.13	0.25

Skill of forecasting river flows

Table 2 clearly shows that there is a strong correlation between SST and river flow. So if the JAS SST of any year can be predicted, the type of flow can be forecasted from that. Since 1980's a number of SST forecast models have been operational which can predict SST with appreciable accuracy. For the assessment of our model for the training period, SST predicted values of the Linear Inverse Model have been used. The results are summarized for 1992 to 2004 in Table 3. The reason for choosing this period is that the Linear Inverse Model is forecasting SST of Nino 4 since 1992.

In order to judge the forecast skill and to compare different forecasts, a synoptic parameter, the Forecasting Index (FI) has been used (Eltahir, 1996). This Index can measure the forecast ability and have previously been used in many other discriminant forecasts. The FI value is defined as the average of the forecasting categoric probabilities for the categories that the observed flood in each individual year falls into during an n-year period. First of all, in each year j (j = 1, 2,….n), the ENSO index are categorized. Accordingly, the probability of each flood category can be forecasted, and are denoted as the prior probability $P_r(i, j)$, where $i = 1$, 2, 3 stand for 3 flow conditions (low, average and high). Then, the flood observation in that year is categorized, and the posterior probability $P_p(i, j)$ can be identified as [1 0 0] in a low flow year, [0 1 0] in an average flow year and [0 0 1] in a high flow year. FP(j), the forecasting probability of the flood category which describes the observed flood condition for that year, can be computed as:

$$FP(j)=\sum_{i=1}^{3}P_r(i,j)P_p(i,j) \tag{1}$$

The Forecasting Index, FI is the average of these probabilities over a certain period:

$$FI=\frac{1}{n}\sum_{j=1}^{n}FP(j) = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{3}P_r(i,j)P_p(i,j) \tag{2}$$

A large Forecasting Index implies a more accurate forecast. A perfect forecasting methodology would have an FI of 1.0. Traditionally, the discriminant forecast skill is measured using the proportion of correct forecasts, in which the right category of the predictand gets the highest predicted probability. Therefore, when the traditional skill measure is used, a forecast of 80% (wet), 15% (average), and 5% (dry) for a wet year is not different from a forecast of 40% (wet), 35% (average) and 25% (dry) because both of the model forecast is wet period. However, the skill measure used in this study can tell the 'accuracy' difference between these different forecasts, even if they might be all correct forecasts. This new measure skill provides a better tool to judge the quality of prediction.

Table 3. Skill of conditional forecast of JAS flow of Brahmaputra-Jamuna, based on predicted SST of Nino 4 (lead time 3-months) (using conditional probability of Table 2)

Year	Predicted JAS SST anomaly	Predicted ENSO condition	Prior Probability of JAS flows			Observed standardized JAS flow	Observed flow category	Posterior probability	FP(j)	FI
			Low	Average	High					
1992	0.594	Warm	0.63	0.13	0.25	–0.06	Average	[0 1 0]	0.13	0.53
1993	0.294	Normal	0.06	0.56	0.38	0.91	High	[0 0 1]	0.38	
1994	0.58	Warm	0.63	0.13	0.25	–1.87	Low	[1 0 0]	0.63	
1995	0.314	Normal	0.06	0.56	0.38	0.30	Average	[0 1 0]	0.56	
1996	–0.066	Normal	0.06	0.56	0.38	1.18	High	[0 0 1]	0.38	
1997	0.744	Warm	0.63	0.13	0.25	–0.38	Average	[0 1 0]	0.13	
1998	–0.603	Cold	0.00	0.00	1.00	2.74	High	[0 0 1]	1.00	
1999	–0.656	Cold	0.00	0.00	1.00	0.57	High	[0 0 1]	1.00	
2000	–0.563	Cold	0.00	0.00	1.00	0.82	High	[0 0 1]	1.00	
2001	0.601	Warm	0.63	0.13	0.25	–1.49	Low	[1 0 0]	0.63	
2002	0.419	Normal	0.06	0.56	0.38	–1.21	Low	[1 0 0]	0.06	
2003	0.025	Normal	0.06	0.56	0.18	–0.49	Average	[0 1 0]	0.56	
2004	0.256	Normal	0.06	0.56	0.38	1.13	High	[0 0 1]	0.38	

The conditional forecasting of JAS flow of Brahmaputra-Jamuna is shown in Table 3. The forecasting index (FI = 0.53) of the conditional probabilities of JAS flow of Brahmaputra-Jamuna is appreciable enough, as FI value equal to or greater than 0.5 indicates a successful forecast (Eltahir, 1996). Another noticeable thing is that among the thirteen events, this discriminant analysis predicts seven events accurately. Thus the overall discriminant analysis substantiates the use of ENSO information for a reasonably successful flow forecast of the Brahmaputra-Jamuna. The forecast indices and especially the performance in forecasting the cold events associated with flood flows certify the practicality of the discriminant forecasting approach for Brahmaputra-Jamuna River.

6. DEVELOPMENT OF STATISTICAL FLOW FORECAST MODEL

The categoric flood prediction using discriminant approach, described in previous section, is certainly an improvement in flood forecasting. This discriminant analysis shows the influence of ENSO on the wet season of Brahmaputra-Jamuna and can forecast the category of flow as high, average or low. Beyond this classification, this type of model cannot predict the size of flow. Therefore development of a long-lead forecast model is necessary, which will be able to forecast the magnitude of flood flow in the wet season.

The approach followed in this study is to first examine the effectiveness of the traditional model, the autoregressive AR(1) model or Markov model (Maass et al., 1962). After examining this method, this research explores the use of teleconnection between flow and ENSO. The primary investigative tool used is the study of correlation. The modeling tool adopted here is combination of autoregression and linear regression. The data from 1977 to 1999 have been used for model development (calibration period) and data of 2000-2004 have been used for verification (verification period).

The JAS flow record of Brahmaputra-Jamuna shows some persistence in data. This is evident from the autocorrelation coefficient (α) of JAS flow which is 0.31. So autoregression can be used to explain a part of flow variability. With this coefficient, the predicted flows using AR(1) model for all the years can explain around 10% (=α^2) of the flow variability. This is the Stage 1 of the model.

In the Stage 2, the analysis is to determine the relationship between flow residuals (i.e., the difference between actual and AR(1) predicted flows) and ENSO, in order to explore the possibility of forecasting the residuals from the predicted SSTs. With this view, linear regressions of the flow residuals with different time-periods SSTs data have been performed and significant relationship is found between flow residuals and JAS SST of Nino 4 region. As SST and flow variability are concurrent, the information provided for the flow at a given time by the autoregressive model and by the SST data are independent. Thus they can be combined for an improved forecasting. The linear regression (Figure 5) shows a correlation coefficient of –0.60 (see Table 4) and can explain 36% of the remaining (i.e., 100–10 = 90%) variability, which amounts to 32%. So the Stages 1 and 2 combine explains a total 42% (= 10+32) of the flow variability where 58% remains unexplained.

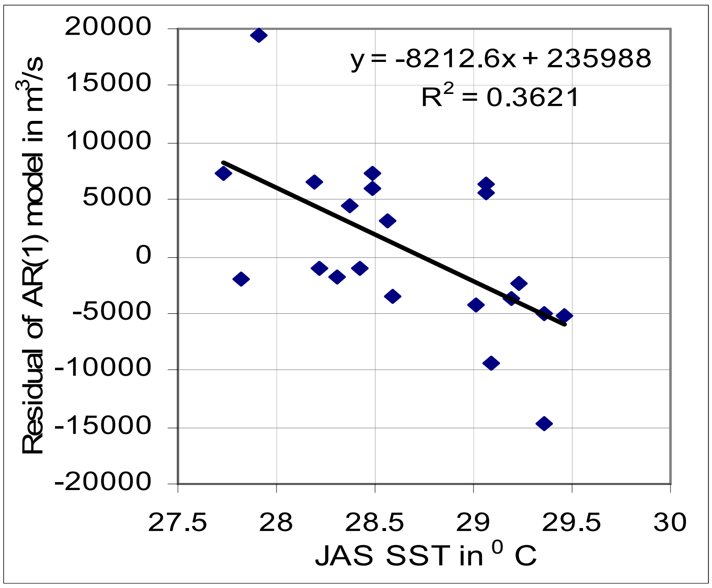

Figure 5. Linear regression between JAS flow residuals and JAS SST of Nino 4 region

The next stage is to find further possibilities of explaining the residuals. There is no significant pattern in the residuals to be captured. At this point an important hypothesis about SST gradient may be adopted. The shift in climatic behavior could be related not only to the magnitude of SST, but also to its gradient, that is, how far SST has been changed in last few months. A qualitative assessment of such predictability has been achieved through examination of stream flows of Amazon, Parana, Congo, Nile (Amarasekera et al., 1998) and Murray Rivers (Chiew et al., 1998). The analysis has been purely statistical, but the physical reason could be that perturbations of transient often have different time scales to reach equilibrium, and perturbations could have diffusive and reverberative characteristics (Whitaker et al., 2001). This approach has been used in the past as a measure of ENSO influence on rainfall (Shukla and Paolino, 1983). Shukla and Mooley (1987) used the difference between April and January Southern Oscillation Index (SOI) as a predictor parameter in their linear regression equation. Whitaker et al. (2001) used SST gradient in conjunction with SST magnitude to identify the impact of ENSO on riverflow. Utilizing these theories, the SST gradient has been used in the Stage 3 of the forecast model. The difference between the JAS SST and March-April-May SST (MAM SST) has been used as SST gradient to capture the residuals of Stage 2 (difference between residuals of Stage 1 and linear regression predicted residuals in Stage 2).

The analysis of the flow residuals with the gradient of SST (Figure 6) yields a correlation coefficient of –0.57, coefficient of determination 0.32, F-statistic value of 9.14 and the p-statistic of 0.007 (Table 4). These values state the statistical significance of the results and certainly improve the forecasting approach. The Stage 3 of the model explains 32% of the remaining unexplained variability which is 19% of the total variability, i.e., 61% (= 42+19) of the total variability becomes explained.

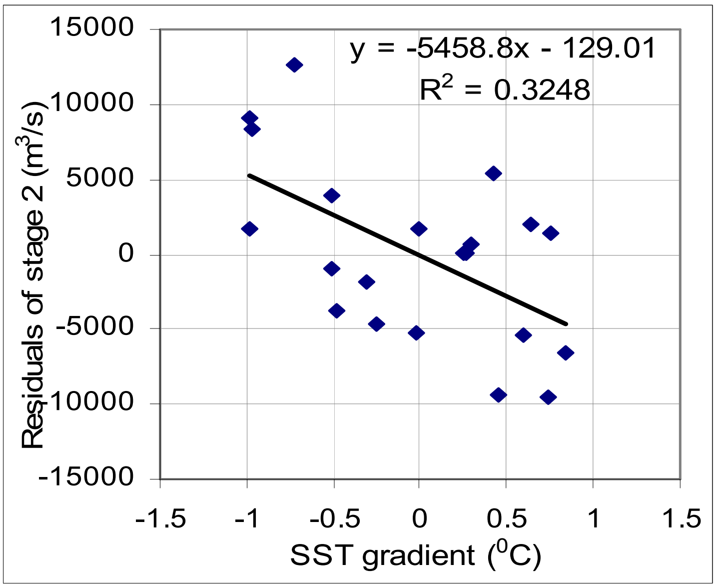

Figure 6: Linear regression between residuals of Stage 2 and SST gradients (difference of JAS SST and MAM SST)

Table 4. Results of linear regression model for the Brahmaputra-Jamuna River

Modeling steps	Dependent variable	Independent variable	Coefficient of regression, R	Coefficient of determination, R^2	F-statistic	p-statistic
Stage 2	AR(1) model residual	JAS SST	–0.60	0.36	10.63	0.004
Stage 3	Stage 2 residual	SST gradient (JAS-MAM)	–0.57	0.32	9.14	0.007

Combining the above mentioned three stages, the average JAS flow of Brahmaputra-Jamuna can be estimated by using the equation as follows

$$Q_{i+1} = \overline{Q} + \alpha\left(Q_i - \overline{Q}\right) - 8212.6\,x - 5458.8\,y + 235859 \quad (3)$$

where, Q_{i+1} is the JAS flow of Brahmaputra-Jamuna in any year in m^3/s, Q_i is the JAS flow of the previous year in m^3/s, $\overline{Q}$ is long-term mean JAS flow in m^3/s, *x* is the JAS SST in °C and *y* is the difference of JAS SST and MAM SST in °C.

Then as an attempt to improve the forecast especially for El Nino and La Nina years, the residuals of Stage 2 have been isolated for El Nino and La Nina years. The linear regression between SST gradients and residuals of Stage 2 for La Nina years attains a coefficient of determination of about 0.43 as shown in Table 5 and explains 25% of the remaining 58% unexplained variability. When it combines with Stages 1 and 2, the combined three stages together explains 67% (= 42+25) of the total variability of JAS flow in a La Nina year. The analysis for the El Nino years has given a very significant result. The resulting coefficient of determination in Stage 3 of the El Nino years is 0.72 (Table 5) and explains 42% of the remaining 58% variability. So the combined three stages explain 84% (= 42+42) of the total variability of JAS flow in an El Nino year.

Table 5. Results of linear regression models for the Brahmaputra-Jamuna River in El Nino and La Nina years

Modeling steps	Dependent variable	Independent variable	Coefficient of regression, R	Coefficient of determination, R^2	F-statistic	p-statistic
Stage 3 (La Nina)	Stage 2 residual	SST gradient (JAS-MAM)	–0.65	0.43	2.25	0.231
Stage 3 (El Nino)	Stage 2 residual	SST gradient (JAS – MAM)	–0.85	0.72	17.80	0.004

Through summing up of the above stages the equation for average JAS flow in a La Nina year is

$$Q_{i+1} = \overline{Q} + \alpha\left(Q_i - \overline{Q}\right) - 8213.9\,x - 8053\,y + 236589 \quad (4)$$

and the equation for average JAS flow in an El Nino year is

$$Q_{i+1} = \overline{Q} + \alpha\left(Q_i - \overline{Q}\right) - 8213.9\,x - 6929.3\,y + 235560 \quad (5)$$

The terms of the equations have their meanings as stated earlier. These equations are capable of estimating JAS flow in m^3/s provided the ENSO conditions can be predicted a prior. The analyses for the El Nino and La Nina years offer an improvement to the accuracy of stream flow forecasting. The F- and p- statistics are significant for El Nino years but not for La Nina years at 0.05 level of significance, although the coefficient of determination is significant. The reason is that the number of observation is only five for La Nina years during the period 1977-1999. The result of this analysis is based on purely statistical correlation. So before giving any definite conclusion more analysis is needed regarding the utility of the equations developed only for El Nino and La Nina years.

7. VERIFICATION OF THE STATISTICAL FORECAST MODEL

As SST is being forecasted efficiently since 1992, the 1992-2004 has been chosen to measure the forecasting efficiency. Here it is important to mention that the calibration period includes years from 1977 to 1999 and verification period from 2000-2004. All the forecasts have been done using Eq (3) for average JAS flow of any year (i.e., without identifying ENSO condition). It means the flow forecasts are made at the first week of the July. At that time, the average JAS SST is predicted. Using those forecasted JAS SST and actual MAM SST, the flow forecasts are made, which are shown in Table 6. However, once ENSO condition is identified for the period concerned, the respective El Nino and La Nina Eqs (4) and (5) can be applied. This has not been applied for this paper for want of more data. Yet again for normal years Eq (3) is to be applied. This model can also be applied for flow forecasting with a lead-time of one-year by using the 12-months lead SST in the Eq (3). This long-lead forecast may have special importance in water resources management.

The flow forecasts of the model with a lead-time of 3-months have been shown in Table 6. The model has shown significant performance in the verification period. The disastrous flood of 1998 has been significantly predicted. The forecast skill of the model with 3-months lead-time is 0.53 and coefficient of determination is 0.55 (shown in Table 7).

Table 6. JAS flow forecasts for Brahmaputra-Jamuna based on the statistical model (Eq 3) with 3-months lead-time

Period	Year	Actual JAS flow (m^3/s)	Forecasted SST (ºC) (lead-time 3-months)		Forecasted JAS flow (m^3/s)	Error in %
			JAS	JAS-MAM		
Calibration period	1992	42616	29.10	– 0.220	44887	5.3
	1993	49164	28.80	– 0.089	42718	– 13.1
	1994	30279	29.08	0.457	39418	30.2
	1995	45001	28.82	– 0.182	39225	– 12.8
	1996	51001	28.44	0.367	43921	– 13.9
	1997	40384	29.25	– 0.151	40312	–0.2
	1998	61619	27.90	– 0.730	52889	– 14.2
	1999	46851	27.85	0.474	53336	– 13.8
Verification period	2000	48556	27.94	0.627	47159	– 2.9
	2001	32840	29.00	0.854	37708	14.8
	2002	34779	28.92	– 0.151	38998	12.1
	2003	39683	28.53	– 0.442	44421	11.9
	2004	50672	28.35	– 0.393	47164	– 6.9

Forecasts of the model with lead-times of 6- and 12- months have been performed, which also show the forecasts are appreciably successful (maximum error < 25%). In some cases the forecasts are better but in general the errors are in rising tendency with the increase of lead-times.

Table 7. Forecast skill of the model for Brahmaputra-Jamuna with 3-months lead-time

Mean squared error	Root mean squared error	Skill	Coefficient of correlation, R	Coefficient of determination, R^2	F-statistic	p-statistic
39789000	6308	0.53	0.74	0.55	12.28	0.006

8. CONCLUSIONS

In this research the teleconnection of ENSO, manifested as an increased propensity of low flow during El Nino and high flow during La Nina, has been established for Brahmaputra-Jamuna River. The correlation analyses between average flow of July-August-September (JAS) and seasonal SSTs show that the JAS flow is highly correlated with JAS SST of Nino 4 region. Discriminant analysis based on the observed flows of 1977-2004 shows that the probability of high flow is 100% in a La Nina year (cold ENSO) and 25% in an El Nino year (warm ENSO). A 3-months lead-time flow forecasting index (FI = 0.53) also indicates a considerably successful forecast.

The statistical flood forecast model based on historical flows and predicted SSTs shows a considerable skill at different lead-times. The accuracy of the forecast decreases with the increase of forecasted lead-time. This is because still no dynamic or statistical SST prediction model has shown excellent skill. This limitation hinders the accuracy of flood forecast with the increase of lead-time. So advanced research is needed to explore the physical mechanism of the ENSO cycle which will in turn increase the predictive skill of ENSO phenomena as well as forecast efficiency of the statistical flood forecast model.

9. REFERENCES

Amarasekera, N.A., R.F. Lee, E.R. Williams, and E.A.B. Eltahir. 1998. ENSO and the natural variability in the flow of tropical rivers. J. of Hydrology, 200, 24-39.

Bari, M.F. and M.M. Hassan. 2005. Role of flood forecasting and warming system in flood hazard mitigation in Bangladesh, Int. Conf. on Monitoring, Prediction and Mitigation of Water-Related Disasters 2005, Dhaka, 227-232.

Chiew, F.HS., T.C. Piechota, J.A. Dracup, and T.A. McMahon. 1998. El Nino/Southern Oscillation and Australian rainfall, stream flow and drought: links and potential for forecasting. J. of Hydrology, 204, 138-149.

Eltahir, E.A.B. 1996. El Nino and the natural variability in the flow of the Nile River. Water Resou. Res. 32: 131-137.

Kiladis, G. and S.K. Sinha. 1991. ENSO, monsoon and floods in India; Chapter 14 in Teleconnections linking worldwide climate anomalies. Ed: M.H. Glantz, R.W. Katz and N. Nicholls. Cambridge University Press.

Maass, A., M.M. Hufschmidt, R.D., H.A. Thomas Jr., S.A. Marglin, and G.M. Fair. 1962. Design of Water Resources Systems. Cambridge, MA, Harvard University Press.

Parthosarathy, B. and G.B. Pant. 1985. Seasonal relationships between Indian summer monsoon rainfall and the Southern Oscillation. J. of Climatology, 5, 369-378.

Rasmusson, E.M., and T.H. Carpenter. 1983. The relationship between eastern equatorial Pacific sea surface temperatures and rainfall over India and Srilanka. Mon. Weather Rev. 111, 517-528.

Ropelewski, C.F., and M.S. Halpert. 1996. Quantifying Southern Oscillation-precipitation relationships, J. Climate, 9, 1043-1059.

Simpson, H.J., M.A. Cane, A.L. Herczez, S.E. Zebiak, and J.H. Simpson. 1993. Annual river discharge in Southeastern Australia related to El Nino-Southern Oscillation forecasts of sea surface temperatures. Water Resou. Res. 29(11): 3671-3680.

Shukla, J., and D.A. Paolino. 1983. The Southern Oscillation and long range forecasting of the summer monsoon rainfall over India. Mon. Weather Rev. 115: 695-703.

Trenberth, K.E. 1997. The definition of El Nino. Bulletin of the American Meteorological Soc. 78(12): 2771-2777.

Whitaker, D.W., S.A. Wasimi, and S. Islam. 2001. The El Nino Southern Oscillation and long-range forecasting of flows in the Ganges. Int. J. of Climatology, 21: 77-87.