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New statistical models for long-range forecasting of southwest monsoon rainfall over India

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Abstract The India Meteorological Department (IMD) has been issuing long-range forecasts (LRF) based on statistical methods for the southwest monsoon rainfall over India (ISMR) for more than 100 years. Many statistical and dynamical models including the operational models of IMD failed to predict the recent deficient monsoon years of 2002 and 2004. In this paper, we report the improved results of new experimental statistical models developed for LRF of southwest monsoon seasonal (June–September) rainfall. These models were developed to facilitate the IMD's present two-stage operational forecast strategy. Models based on the ensemble multiple linear regression (EMR) and projection pursuit regression (PPR) techniques were developed to forecast the ISMR. These models used new methods of predictor selection and model development. After carrying out a detailed analysis of various global climate data sets; two predictor sets, each consisting of six predictors were selected. Our model performance was evaluated for the period from 1981 to 2004 by sliding the model training period with a window length of 23 years. The new models showed better performance in their hindcast, compared to the model based on climatology. The Heidke scores for the three category forecasts during the verification period by the first stage models based on EMR and PPR methods were 0.5 and 0.44, respectively, and those of June models were 0.63 and 0.38, respectively. Root mean square error of these models during the verification period (1981–2004) varied between 4.56 and 6.75% from long period average (LPA) as against 10.0% from the LPA of the model based on climatology alone. These models were able to provide correct forecasts of the recent two deficient monsoon rainfall events (2002 and 2004). The experimental forecasts for the 2005 southwest monsoon season based on these models were also found to be accurate.

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1 Introduction

In an agricultural country like India, the success or failure of the crops and water scarcity in any year is always viewed with the greatest concern. A major portion of annual rainfall over India is received during the southwest monsoon season (June–September). Regional rainfall has large year-to-year fluctuations. However, the southwest monsoon rainfall over the country as a whole is more or less stable. The mean seasonal rainfall (based on 1941–1990 data) averaged over the country as a whole is 89 cm with a coefficient of variation of about 10%. However, even this small fluctuation in the seasonal rainfall can have devastating impacts on agricultural sector. Even though, the contribution from the agricultural sector to the national income has decreased over the years (less than 30% now), the performance of the agricultural sector is still very critical to India's economy. The deficient monsoon rainfall during the recent 2 years (2002 and 2004) has had an adverse impact on India's economy. Therefore, long-range forecasting (LRF) of southwest monsoon rainfall is a high priority in India. An accurate forecast of monsoon performance averaged over the country as a whole is also very useful for better macro level planning of finance, power and water resources.

The India Meteorological Department (IMD) has been issuing LRF of the southwest monsoon rainfall since 1886. It was, however the extensive and pioneering work of Gilbert Walker (1923, 1924), that led to the development of the first objective models based on statistical correlations between monsoon rainfall and antecedent global atmosphere, land and ocean parameters. Since then, IMD's operational LRF system has undergone changes in its approach and scope from time to time. There are many reviews on the LRF of Indian southwest monsoon rainfall (ISMR) (Normand 1953; Jagannathan 1960; Thapliyal and Kulshreshtha 1992; Hastenrath 1995; Krishna Kumar et al. 1995; Rajeevan 2001; Gadgil et al. 2005). In a very recent study, Gadgil et al. (2005) addressed the major problems of the statistical and dynamical methods for LRF of monsoon rainfall in view of the recent forecast failures in 2002 and 2004. Their analysis revealed that IMD's operational forecast skill based on statistical methods has not improved over seven decades despite continued changes in the operational models.

For the LRF of the ISMR, three main approaches are used. The first is the statistical method, which uses the historical relationship between the ISMR and global atmosphere–ocean parameters (Walker 1914, 1923; Thapliyal 1982; Gowariker et al. 1989, 1991; Navone and Ceccatto 1995; Singh and Pai 1996; Guhathakurta et al. 1999; Rajeevan et al. 2000, 2004, 2005; Delsole and Shukla 2002; Sahai et al. 2003; Pai and Rajeevan 2006). The second approach is the empirical method based on a time series analysis. This method uses only the time series of past rainfall data (Goswami and Srividya 1996; Iyengar and Raghukanth 2004; Kishtawal et al. 2003) and do not use any predictors. The third approach is based on the dynamical method, which uses general circulation models of the atmosphere and oceans to simulate the summer monsoon circulation and associated rainfall. In spite of its inherent problems, at present, statistical models perform better than the dynamical models in the seasonal forecasting of ISMR. The dynamical models have not shown the required skill to accurately simulate the salient features of the mean monsoon and its interannual variability (Latif et al. 1994; Gadgil and Sajani 1998; Krishnamurti et al. 2000; Kang et al. 2002; Gadgil et al. 2005; Krishna Kumar et al. 2005; Wang et al. 2005).

During the period of 1988–2002, IMD's operational forecasts were based on the 16-parameter power regression and parametric models (Gowariker et al. 1989, 1991). The forecasts issued during this period were qualitatively correct. However, the mean forecast error during this period was more than the mean error of the forecasts based on climatology alone. This model failed to predict the severe drought of 2002. Following the failure of forecast in 2002, a critical evaluation of the 16-parameter power regression and parametric models was made and in 2003, two new models (8 and 10 parameter models) were introduced for the operational work. Further a two-stage forecasting strategy was also adopted with the provision for a forecast update by end of June/first week of July (Rajeevan et al. 2004). According to this new strategy, IMD's operational forecasts for the seasonal ISMR for the country as whole are issued in two stages. The first stage forecast is issued in mid April and an update or second stage forecast is issued by the end of June. While the 2003 and 2005 operational forecasts for the southwest monsoon rainfall based on these new models were accurate, the forecast for the 2004 monsoon came up false.

Following the failure of the operational forecast in 2004, two major issues were critically analyzed; (a) a re-visit of the identification of predictors, which have physical relationships with monsoon rainfall in view its weakening of relationship with ENSO (Krishna Kumar et al. 1999) and (b) a critical look at the development of models in terms of the optimal number of predictors and the model development period, etc. We also further explored new statistical methods in the hope of improving model performance.

In this paper, we discuss the details of the new experimental models for the LRF of ISMR. These new statistical models are based on the following techniques:

(1) Ensemble multiple linear regression (EMR)
(2) Projection pursuit regression (PPR)

In Sect. 2, we discuss the data used for this study and in Sect. 3, we discuss the details of the predictors used in the new experimental models. Various methods used for model development and model forecast verification are discussed in Sect. 4. In Sect. 5, results from the new forecast models are discussed. Finally, the conclusions are presented in Sect. 6.

2 Data used

The southwest monsoon season (June–September) rainfall over the country as a whole (ISMR) is calculated as the area weighted average of the seasonal monsoon rainfall data of all 36 meteorological subdivisions in India. The long period average (LPA) (1941–1990) of the seasonal rainfall is 89 cm and the coefficient of variation is about 10%. The ISMR was expressed as the percentage departure from the LPA. We used ISMR series for the period from 1958 to 2005. The ISMR series used in the study is different from another widely used ISMR series of Parthasarathy et al. (1995), which used a fixed a network of 306 raingauge stations over the plains of India. IMD ISMR series of IMD was constructed from a network of around 2,000 raingauges distributed all over India including the hilly regions. However, the correlation coefficient (CC) between these two ISMR time series for the period of 1958–2003 is highly significant (0.98).

In terms of identifying predictors, we have used monthly data sets of various parameters such as sea surface temperature (SST), mean sea level pressure, zonal wind at 850 hPa and station level surface air temperatures. The SST data set used was the monthly NOAA Extended Reconstructed Global Sea Surface Temperature version 2 (ERSST.v2) data at 2°×2°, latitude × longitude grid (Smith and Reynolds 2004). These data were obtained from the National Climatic Data Center (NCDC), Asheville, NC, USA (http://www.ncdc.noaa.gov/oa/climate/research/sst/sst.html/). The monthly surface sea level pressure and 850 hPa zonal wind data of NCEP/NCAR reanalysis (Kalnay et al. 1996) were obtained from the NOAA-CIRES Climate Diagnostics Center, Boulder, CO, USA (http://www.cdc.noaa.gov/). The spatial resolution of these data is 2.5°×2.5° latitude × longitude.

In addition, we have used the monthly mean warm water volume (WWV) data over the Pacific (Meinen and McPhaden 2000; McPhaden 2003; Rajeevan and McPhaden 2004). The WWV data available on real time at http://www.pmel.noaa.gov/tao/elnino/wwv/ were based on the upper ocean temperature field analysis (McPhaden et al. 1998). Another data that we used were the monthly land surface air temperatures of five stations from Europe obtained from the publication 'World Climatic Data for the world' published by the NCDC. These stations are: Orland, Oslo/Gendermon, Ostursund/Froson, Karlstad and De Bilt. We also used the monthly mean Nino-3.4 index data obtained from the Climate Prediction Centre, NOAA (http://www.cpc.ncep.noaa.gov/). All the above monthly data were used for the period of 1958–2006.

3 Details of predictors

The main aim of the development of the new forecast models for the LRF of ISMR was to support IMD's present two-stage forecasting system, which demands two sets of models. The first set is useful for the first stage forecast issued in mid April and the second set for the second stage or update forecast issued by the end of June.

For the first stage forecast models, a predictor set requiring data up to March (SET-I) was used and for the second stage forecast models, another predictor set requiring data up to May (SET-II) was used. The list of the predictors in the SET-I and SET-II is given in Tables 1 and 2, respectively. There are nine predictors in total. Figure 1 shows the geographical regions of these predictors. Each of these predictor sets contains six predictors each. The first three predictors are common in both the data sets. In the SET-II, the last three predictors require data up to May. As seen in Tables 1 and 2, all the predictors have significant (>5% is a significant level) correlations with the ISMR. The correlations were computed for the period from 1958 to 2000. The SST predictors were derived as the simple arithmetic average of the monthly ERSST.v2 anomalies over the respective geographical region. The time periods used for the averaging are given in the third column of Tables 1 and 2. The pressure and wind predictors were similarly derived from the NCEP

Table 1 Details of predictors used for the first stage forecast (SET-I)

No.	Parameter	Period	Spatial domain	CC with ISMR (1958–2000)
A1	North Atlantic SST anomaly	December + January	20N–30N, 100W–80W	–0.45**
A2	Equatorial SE Indian Ocean SST anomaly	February + March	20S–10S, 100E–120E	0.52**
A3	East Asia surface pressure anomaly	February + March	35N–45N, 120E–130E	0.36*
A4	Europe land surface air temperature anomaly	January	Five stations	0.42**
A5	Northwest Europe surface pressure anomaly tendency	DJF(0) – SON (–1)	65N–75N, 20E–40E	–0.40**
A6	WWV anomaly	February + March	5S–5N, 120E–80W	–0.32*

*Significant at and above 5% level

**Significant at and above 1% level

Table 2 Details of predictors used for the second stage forecast (SET-II)

No.	Parameter	Period	Spatial domain	CC with ISMR (1958–2000)
J1	North Atlantic SST anomaly	December ++ January	20N–30N, 100W–80W	–0.45**
J2	Equatorial SE Indian Ocean SST anomaly	February ++ March	20S–10S, 100E–120E	0.52**
J3	East Asia surface pressure anomaly	February ++ March	35N–45N, 120E–130E	0.36*
J4	Nino-3.4 SST anomaly tendency	MAM(0) – DJF(0)	5S–5N, 170W–120W	–0.46**
J5	North Atlantic surface pressure anomaly	May	35N–45N, 30W–10W	–0.42**
J6	North Central Pacific zonal wind anomaly at 850 hPa	May	5N–15N, 180E–150W	–0.55**

*Significant at and above 5% level

**Significant at and above 1% level

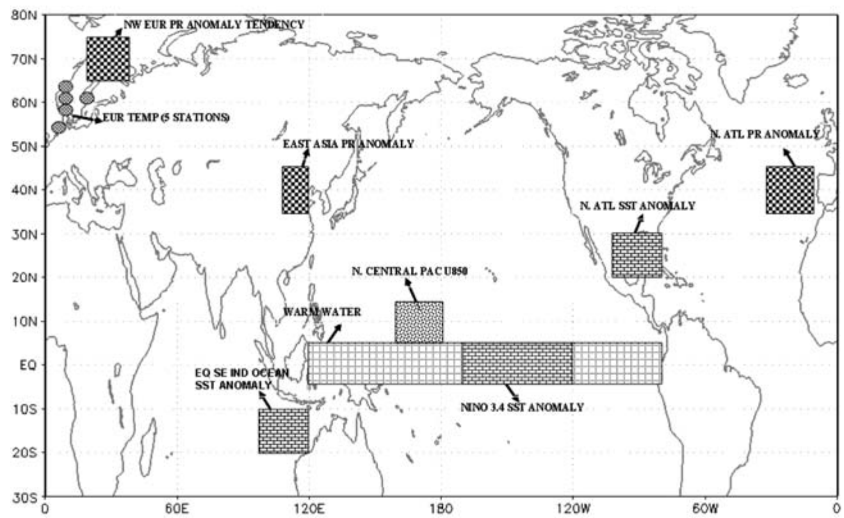


Fig. 1 Geographical locations of the nine predictors listed in Tables 1 and 2

reanalysis data. The land surface air temperature anomaly over the Northwest Europe was computed as the average of surface air temperature anomalies of the five land stations from Europe. The seasonal tendency in the Nino-3.4 anomaly index was computed by subtracting monthly anomalies averaged over the winter season (DJF) from those averaged over the spring season MAM (March–May). The WWV anomaly over the Pacific (February + March) was derived from the monthly averages of WWV computed between 5°N and 5°S integrated across the Pacific basin including all ocean areas between 120°E and 80°W (Rajeevan and McPhaden 2004). The lower boundary for this integration is the depth of the 20°C isotherm, which is located in the middle of the upper thermocline. All anomalies were computed using the climatological base period of 1971–2000. One of the SST predictors (southeast Indian Ocean) common in both the predictor sets showed a significant warming trend during the data period. Hence, the time series of this predictor only was de-trended by removing the linear trend fitted for the period of 1958–2000 from the time series.

Figure 2 shows the 21-year moving CC between ISMR and the nine predictors selected for the model development. The horizontal dashed lines represent the CC (±0.43) significant at a 5% level. As seen in Fig. 2, the relationship of most of the predictors with ISMR was stable (CC near or above 5% significant level) during the entire period particularly during the recent years. A brief discussion on the physical linkage between the predictors and ISMR is given in the research report by Rajeevan et al. (2005). There are significant inter-correlations among some of the predictors. This can be seen in Table 3, which depicts the lower triangle of the inter-correlation matrix of all the nine predictors used in both the SET-I and SET-II together. CC values significant at and above 5% level are shown by bold letters. Before using these predictors in the models, all the predictor time series were standardized using the base period data of 1971–2000.

4 Methodology

4.1 EMR models

The EMR models for the first and second stage forecasts (EMR-I and EMR-II, respectively) were

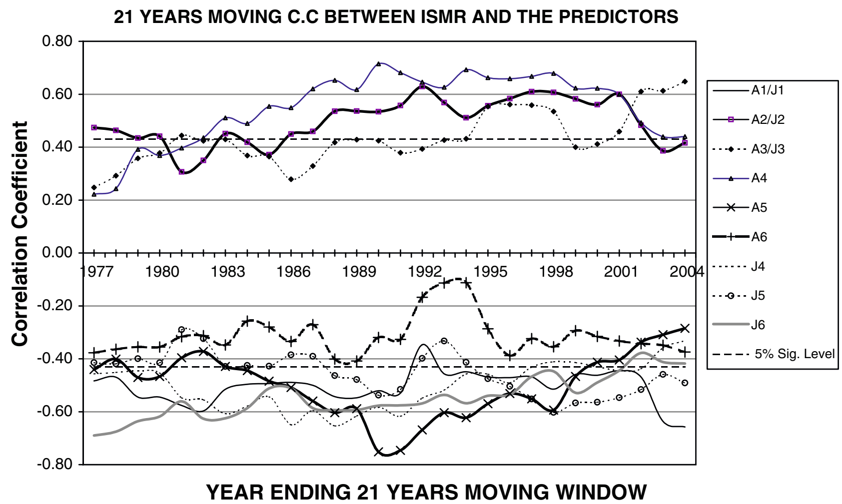


Fig. 2 The 21 years moving correlations between the predictors listed in Tables 1 and 2 and ISMR. The *horizontal dashed lines* represent the correlation significant at 95% level

Table 3 Inter-correlation among the predictors used in SET-I and SET-II

	A1/J1	A2/J2	A3/J3	A4	A5	A6	J4	J5	J6
A1/J1	1.00								
A2/J2	0.02	1.00							
A3/J3	–0.29	0.18	1.00						
A4	–0.04	0.16	0.23	1.00					
A5	0.05	–0.06	0.04	**–0.69**	1.00				
A6	0.22	**–0.47**	–0.07	–0.06	–0.01	1.00			
J4	0.24	**–0.53**	–0.18	–0.14	–0.03	**0.61**	1.00		
J5	0.22	–0.06	–0.17	**–0.39**	**0.46**	0.21	0.01	1.00	
J6	0.08	**–0.47**	–0.04	–0.20	0.06	0.17	0.12	0.03	1.00

Period: 1958–2000. CC values significant at and above 5% level are shown in bold letters

developed using the predictor sets of SET-I and SET-II, respectively, with six predictors. On the way to the development of the EMR models we have addressed the following two important issues; (a) what is the optimal length of training period for a given model? (b) Given the six predictors, how does one select a set of best models (members of ensemble) out of all possible multiple regression (MR) models?

Kung and Sharif (1982) and McBride and Nicholls (1983) have highlighted the need for regular training or updating of the forecast models with the latest data for better forecasts. The necessity of updating model equations is due to the fact that the time series of meteorological parameters are statistically nonstationary. The instability of the meteorological series suggests that the use of all available data for the development of forecast equation might not automatically improve its performance. A near optimal length of training period has to be identified (Nicholls 1984). Therefore, our first aim was to find out the optimal length of training period for all the possible MR models constructed using each of the predictor sets (SET-I and SET-II).

For 'p' standardized predictors for 'n' years, the MR model equation can be written as

$$\mathbf{Y}(z_1, z_2, z_3, \ldots, z_p) = \sum_{i=1}^{p} \boldsymbol{\alpha}^{\mathrm{T}}\mathbf{Z} \quad (1)$$

where $\mathbf{Y}$ is the $(n \times 1)$ predictand (ISMR) matrix, α^{T} is the $(p \times 1)$ row matrix of regression coefficients, and $\mathbf{Z}$ is the $(n \times p)$ matrix of 'p' predictor variables.

If there are 'p' predictors, it is possible to build $(2^p - 1)$ MR models relating the predictors and predictand by making use of all possible combinations of the predictors. Using six predictors, it is possible to build 63 $(=2^6 - 1)$ MR models. To find out the optimal length of training period, the predictive skill of each of the all possible models during a fixed common period 1981–2004 was examined. For this, we have used the sliding model training period technique for all the possible lengths of training period. For example, for the case of training period of 15 years length, data for 1971–1985 were used for predicting rainfall of 1986 and data for 1972–1986 were used for predicting the rainfall of 1987 and so on. We have used the root mean square error (RMSE) of the forecasts for the period 1981–2004 as the measures of predictive skill (equation for the computation of RMSE is given in Sect. 4.3). For each of the possible models, RMSE values were computed for different lengths of training period. For each model, the optimal length of training period is taken as that length of training period for which the RMSE of forecasts for the period 1981–2004 is the lowest.

Figure 3 shows the scatter diagram of RMSE of all the possible models (63 models) derived from SET-I plotted against different model training period lengths (from 8 to 28 years). The solid line shows the mean value of the RMSE obtained by averaging across all the 63 models. In Fig. 3, it is seen that the RMSE of the models decreases with increase in the length of training period and reaches the minimum value around 23 years and then again increases with increase in the length of training period. A similar analysis with all the possible MR models derived from the SET-II (not shown) also showed that the optimal length of training period is around 23 years.

Now, we discuss the methodology for selecting a set of best models out of all possible models. When a set of '*p*' predictors are available, the typical approach used in the model development is to use a selection exercise leading to a single 'best' model and then make inferences assuming that the selected model is the true model. The best model may be one that explains the highest variance during the development period or one that having the highest predictive skill during an independent data period. The selection of the best subset of predictors or optimal number of predictors in the statistical models is discussed by many researchers (Hastenrath and Greischar 1993; Delsole and Shukla 2002). For monsoon forecast, these studies suggested that three or four predictors are adequate for developing a statistical model with useful skill. Delsole and Shukla (2002) discussed the major issue of over-fitting in the IMD's previous operational model in which as many as 16 predictors were used for the model development (Gowariker et al. 1989, 1991). They have recommended use of a small number of predictors for model development.

However, the use of a single best model ignores a major component of uncertainty, namely uncertainty about the model itself (Draper 1995; Raftery 1996) which results in the underestimation of the uncertainties about the model inferences. A solution to this problem is to average over all possible models when making the predictand inferences (Madigan and Raftery 1994). Alternatively, a lesser number of models can be selected from all possible models for averaging to obtain inferences about the predictand that are very close to the inferences which would have been achieved by averaging over all possible models. Raftery et al. (1997) proposed two methods as alternate approaches of Bayesian model averaging of linear regressions. The first method is an ad hoc procedure called 'Occam's Window', which indicates a small set of models over which a model average can be computed. The second method is Markov Chain Monte Carlo approach which directly approximates the exact solution.

In this paper, best models for ensemble average were obtained in two steps. In the first step, models were ranked based on the objective criteria of likelihood function or generalized cross-validation (GCV) function (Singhrattna et al. 2005). GCV can be computed as given below,

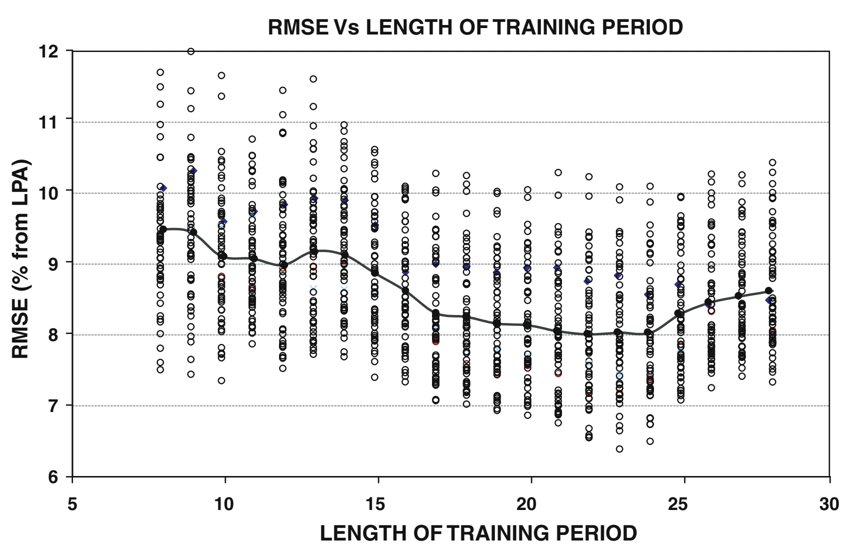


Fig. 3 *Scatter plot* of RMSE of the forecasts by each of all possible models derived from SET-I for training period of different lengths (from 8 to 28 years). The *solid curve* connects the average RMSE of all the possible models. The RMSE was computed for the period 1981–2004

$$\mathrm{GCV} = \frac{\sum (Y' - Y)^2 / n}{(1 - p/n)^2} \tag{2}$$

where Y' is the model forecast obtained using sliding training period method with an optimal window period of length 23 years. GCV is nearly equal to the square of the RMSE with a correction for the number of predictors used in the model. GCV for the period 1981–2004 was calculated for all the possible MR models and the models were ranked in the ascending order of GCV values. The model with lowest value of GCV was ranked first and model with highest value of GCV was ranked last (63rd). Figure 4 shows the scatter plot of GCV values against the rank of the model. The light (dark)-shaded markers correspond to models derived from SET-I (SET-II). It is seen that, models tend to cluster in groups with some breaks. This is more evident for the model with SET-II parameters. In the case of models derived from SET-I, the first break is seen after the cluster of first four models. In case of the models derived from SET-II, the first break is seen only after the cluster of first 13 models.

In the second step, ensemble average of forecasts from the models ranked based on GCV values was computed for the period 1981–2004 by using first 1 model, first 2 models, first 3 models and so on up to all the possible 63 models in the rank list as the ensemble members. The ensemble average for each year of the independent period 1981–2004 was computed as the weighted average of the forecasts from the individual ensemble members. The weighted average is calculated as

$$Y'_{\mathrm{E}} = \frac{\sum_{i=1}^{i=k} w_i Y'_i}{\sum_{i=1}^{i=k} w_i} \tag{3}$$

where 'Y'_{E}' is the ensemble forecast for a given year, 'Y'_i' is the corresponding forecast by ith of the 'k' ensemble member models and w_i's are the weights. Here, we have used the adjusted R of the model during the training period as the weights. Adjusted R is the multiple CC (R) adjusted for the number of predictors used in the model. The relation between R and adjusted R is given as: (adjusted $R)^2 = R^2 - p(1- R^2)/(n-p-1)$, where '$n$' is the length of the training period (i.e., 23 years) and 'p' is the number of predictors used in the model. The weights of each model can vary with the year for which forecast is made as we have used a sliding training period.

Figure 5 shows the RMSE of the ensemble average of forecasts plotted against the ensemble size (number of models in the ensemble). The solid (dotted) line corresponds to models derived from SET-I (SET-II). As seen in Fig. 5, the RMSE (6.48% of LPA) is the highest for the two-member ensemble and decreases to its lowest value (5.47% of LPA) for the four-member ensemble. Further increase in the ensemble size increases the RMSE of ensemble model. This suggests a natural break point near ensemble size of 4. Similar kind of inference was obtained in Fig. 4. Thus, we have considered these four MR models for building the ensemble model, EMR-I.

Similarly in Fig. 5, as revealed by the dotted line, one-member ensemble has the highest RMSE (5.66% of LPA). The RMSE shows a general decrease in

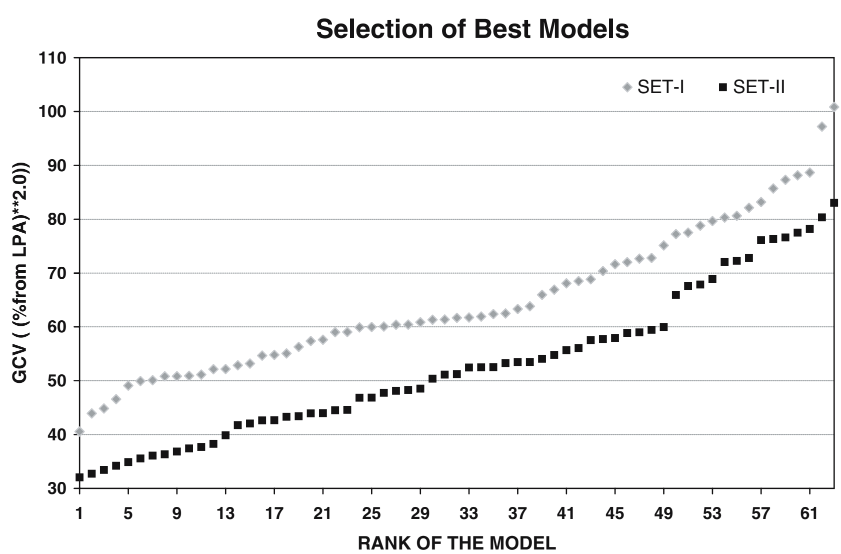


Fig. 4 *Scatter plot* of GCV against rank of the models arranged as per the ascending values of GCV. The *light* (*dark*)-*shaded* markers are for models derived from SET-I (SET-II). The GCV was computed for the period 1981–2004

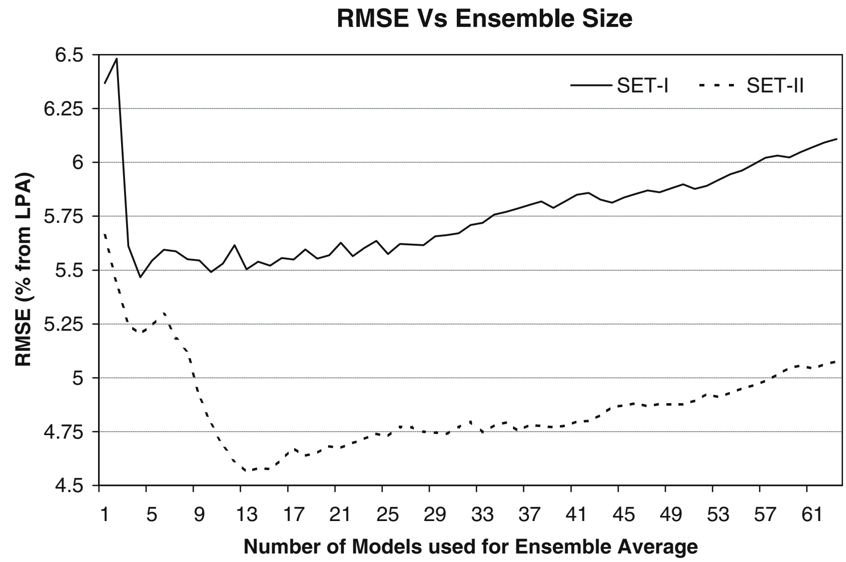


Fig. 5 *Line plots* of RMSE of the ensemble average of forecasts against the ensemble size. The *solid* (*dotted*) *line* is for models derived from SET-I (SET-II). The RMSE was computed for the period 1981–2004

RMSE with increase in the ensemble size to reach its lowest value (4.56% of LPA) for the 13-member ensemble. Further increase in the ensemble size shows increase in the RMSE. Thus, in the case of models derived from SET-II, the natural break point is reached at ensemble size of 13 (as was the case depicted by the dark-shaded makers in Fig. 4). Therefore, these 13 MR models were selected to build the ensemble model, EMR-II. Details of the selected models for building EMR are discussed in Sect. 5.

4.2 PPR models

We also considered another statistical technique to develop a model for seasonal forecasts. The purpose was to develop an independent nonlinear model, with a different methodology.

The projection pursuit (PP) was first proposed by Friedman and Tukey (1974). The basis of the PP technique is the linear projection of the data. However, it attempts to identify the nonlinear structures within the projections. The name 'projection pursuit' is associated to the fact that the technique automatically pursues the most 'interesting' projections. Huber (1985) proposed PP as an alternative to the traditional principal component technique to reduce a high-dimensional data set into a lower-dimensional one. One such application of this method was the PPR. This new method of nonparametric MR was proposed by Friedman and Stuetzle (1981). Chan et al. (1998) demonstrated that PPR is superior to traditional MR analysis, because the PPR is capable of identifying nonlinear relationships between the predictand and the predictors. Chan and Shi (1999) used this technique to develop models for forecasting of summer monsoon rainfall over south China and obtained skillful results. The PPR is based on the iterative estimation of linear combinations of the original predictor variables and the corresponding smooth functions that describe the relation between the projection and the response.

The PPR has the form

$$\mathbf{Y}(z_1, z_2, z_3, \ldots, z_p) = \sum_{m=1}^{M} f_m(\boldsymbol{\alpha}_m^{\mathrm{T}}\mathbf{Z}) \tag{4}$$

where $\mathbf{Z}$ is the $(n \times p)$ matrix of 'p' predictor variables and α_m^{T} is the $(p{\times}1)$ row vector. The projection $\alpha_m^{\mathrm{T}}\mathbf{Z}$ gives the linear combination of the predictor variables. The smooth f_m applied on this projection are the single-valued (ridge) functions of a single variable. M is the total number of projections and smooths needed to be able to describe variation in a response variable. The vector α_m^{T} is fitted by nonlinear fitting such as Gauss–Newton and the function f_m is fitted by the curve-fitting such as splines. Friedman's initial implementation of PPR used super-smoother (Friedman 1984) for fitting f_m. Roosen and Hastie (1994) used smoothing splines for the same purpose.

The PPR is identical to a three-layer perceptron or feed forward neural network (Bishop 1995). In neural network, the function f_m is called activation functions. The only difference is that in neural networks the function f_m is the same for all the nodes, while in PPR it can differ for each of the M projections; its format is more flexible and data-driven.

An iterative algorithm defines the exact fitting of model terms. The fitting procedure alternates between an estimation of the vector α_m^{T} and an estimation of function f_m. The function f_m is continuous in the model, but in the algorithm only its values at the data points are used. The fraction of unexplained variance that is explained by adding the term $f_m(x)$ can be used as a criterion of fit (figure of merit):

$$I(\boldsymbol{\alpha}_m) = 1 - \sum_{i=1}^{n} (r_i - f_m(\boldsymbol{\alpha}_m^{\mathrm{T}}\mathbf{Z}))^2 \bigg/ \sum_{i=1}^{n} r_i^2 \tag{5}$$

where r_i is the residual. The M projections and smooths are produced in a stepwise procedure. The iteration process is initiated by setting $r_i = Y_i$ (assuming that the response is centered: $\sum Y_i = 0$). The vector α_m^{T} and the corresponding smooth $f_m(x)$ that maximize $I(\alpha_m)$ are selected and the process is terminated when $I(\alpha_m)$ is smaller than a user specified threshold. As long as $I(\alpha_m)$ is not smaller than a threshold value, the residuals are calculated as r_i=-Y_i $- f_m(\alpha_m^{\mathrm{T}}\mathbf{Z})$. These residuals are then used as the response values in the next step of the stepwise procedure.

In this study, we have used the R software (http://www.cran.r-project.org/) MASS library to derive the PPR model.

Two PPR models were developed, one for the first stage forecasts (PPR-I) in April using the SET-I data and second for the second stage forecast (PPR-II) in June using the SET-II data. In this study, M was set to 2 (representing two projections, the maximum being p, which is the number of potential projections) as the inclusion of more projections did not further increase the variance explained. Thus the predictand was expressed as the sum of the functions of first two projections. The independent forecasts were produced by sliding the training period with an optimal window period of length 23 years as done in the EMR models.

4.3 Verification of the model forecasts

The model forecasts during the period 1981–2004 were verified using simple model statistics such as CC between actual and predicted ISMR (R), bias in the model forecasts (BIAS) and RMSE. They are calculated in the following way.

$$R = \frac{\sum \left(Y - \bar{Y'}\right)\left(Y - \bar{Y}\right)}{\sqrt{\sum \left(Y - \bar{Y'}\right)^2 \sum \left(Y - \bar{Y}\right)^2}} \tag{6}$$

$$\mathrm{BIAS} = \frac{\sum (Y' - Y)}{n} \tag{7}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum (Y' - Y)^2}{n}} \tag{8}$$

where $\bar{Y}$ and $\bar{Y'}$ are the sample averages of the Y and Y', respectively.

Another method of verification used in this study was a three-way category forecast verification. In this verification method, the forecasts were made into three pre-defined rainfall categories of equal probabilities (33.3%). In this case, there were 24 years (1981–2004) for verification and therefore the rainfall categories were so formed that each of the categories contained 8 years. The three categories used were (a) below normal (<-7.45% from LPA), (b) normal (-7.45–1.45% from LPA) and (c) above normal (>1.45% from LPA).

The verification statistics used for the category forecasts were (a) hit score (HS), (b) Heidke skill score (HSS), (c) probability of detection (POD) and (d) false alarm rate (FAR). HS is the proportion of the correct forecasts and is computed as the ratio of forecasts in the correct category to the total number of forecasts. The HSS is the HS adjusted to account the proportion of forecasts that would have been correct by chance in the absence of skill and is computed as [(3/2) × HS] - 1/2. For a good model, the HSS should be more than 0.33 (i.e., 1/3rd of the forecasts are categorically correct). The POD explains the goodness of the model to detect a pre-defined category. POD for below normal category is the probability of the model forecasting below normal when below normal rainfall was observed. Similarly, we can also define POD for the above normal category. FAR for a forecast category is the measured as the percentage of the total forecasts in that category which were opposite to the observed category. FAR for a below (above) normal forecast is the percentage of the forecasts made in that category for which observed category was above (below) normal.

5 Results and discussions

5.1 EMR models

Tables 4 and 5 show the details of the ensemble members (MR models with least GCV) used to construct the ensemble models EMR-I and EMR-II, respectively. In Table 4, there are four models. It can be seen that one predictor (East Asia surface pressure anomaly) is common in all these four models and that only five out of six predictors of SET-I have been used to derive these models. Northwest Europe surface pressure anomaly tendency has not been used in any of the four models. In Table 5, two predictors (East Asia surface pressure anomaly and North Atlantic surface pressure anomaly) are common in all the selected 13 models. The forecast of EMR-I was computed as the weighted average of the forecasts of the four models given in Table 4 and that of EMR-II was computed as the weighted average of the forecasts of 13 models given in Table 5.

The forecasts of EMR-I model are shown in Fig. 6a, along with the forecasts of its ensemble members (four MR models) used for building the EMR model. Similarly Fig. 6b shows the forecasts of EMR-II model along with the forecasts of its 13 ensemble members.

As seen in Fig. 6a, during all the extreme years like 1982, 1983, 1986, 1987, 2002 and 2004, both the individual forecasts as well as their ensemble average showed the same sign as that of the actual ISMR. Even the magnitudes were mostly closer to the actual values. The advantage of the ensemble forecast was more evident during some of the extreme years like 1983, 1987, 2004, etc. In case of 1983, the ensemble member forecasts ranged from 6.14 to 15.7% from LPA, whereas the ensemble average was 12.02%, which was closer to the actual value. For 1987, the ensemble member forecasts ranged from –9.55 to –19.65% from LPA, whereas the ensemble average was –13.72%, which was closer to the actual value. As such the ensemble method almost provides practically better forecasts than the individual ensemble members (MR models). However, there are years like 1981, 1985, 1992 and 1997 when the sign of the ensemble average was opposite to that of the actual average. During all these years (except 1997), the actual values of ISMR were on negative side and the forecasts were on positive side, indicating a positive bias (see Table 6) in the forecasts using the EMR-I model.

As seen in Fig. 6b, EMR-II forecasts and most of the ensemble member forecasts showed the same sign as that of the actual ISMR during most of the years. The magnitude was also closer to actual values. It can be noted that the bias of the EMR-II was very small (see Table 6). However, during 5 years (1981, 1985, 1989, 1997 and 2003) the sign of the EMR-II forecasts was opposite to that of the actual ISMR. The forecast was an over-estimate during 2 years (1981 and 1985) and an under-estimate during the remaining years.

Table 6 shows the model forecast verification statistics of EMR-I and EMR-II models computed for the period 1981–2004. Though the value of R for both the ensemble models was nearly the same, the RMSE of the EMR-II (4.56% from LPA) was appreciably less than that of EMR-I (5.47% from LPA). This indicates that the performance of the EMR-II during the verification period was better than that of EMR-I model. The RMSE of forecasts for the same period based on climatology alone was 10% from LPA, which is almost double the RMSE of the ensemble models. The climatological forecast for a given year was obtained as the average of ISMR during the preceding 23 years to the given year. Thus, the performance of both the EMR models was far better than that of the model based on climatology alone. This is also reflected in the three category forecast by the EMR models. As seen in Table 6, the HS and HSS of the EMR-II (75% and 0.63) were higher than that of EMR-I (67% and 0.5). Both the EMR models did not produce any false alarms in both the below normal and above normal categories. Similarly for both the models, the POD the below normal category was 100%. The POD above normal category was 77% for EMR-I and 82% for EMR-II.

5.2 PPR Models

As in the case of the EMR model, 23 years were used as the optimal length of training period and the sliding training period technique was used to produce independent forecasts. During each of the 23 years model training periods, its was observed that the relationship between the first projection predictor $\mathbf{X}_1 - \alpha_1^{\mathrm{T}}$ and ISMR was linear and that between the residual $r(z) = \mathbf{Y} - f_1(\alpha_1^{\mathrm{T}}\mathbf{Z})$ obtained after removing the contribution of $\mathbf{X}_1$ in the ISMR and the second projection predictor $\mathbf{X}_2 = \alpha_2^{\mathrm{T}}\mathbf{Z}$ was nonlinear. These two relationships for the case of the model trained (using the

Table 4 Details of the four models selected from all possible MR models constructed using the predictors of SET-I for building the EMR-I model

Regression model	No. of predictors	Predictors	Model skill (1981–2004)	
			GCV (% from LPA)*2	CC (R)
Model 1	4	A1, A2, A3 and A6	40.55	0.79
Model 2	3	A1, A2 and A3	43.93	0.78
Model 3	4	A2, A3, A4 and A6	44.83	0.82
Model 4	3	A3, A4 and A6	46.58	0.76

Table 5 Details of the ensemble of 13 MR models selected for building EMR-II

Regression model	No. of predictors	Predictors	Model skill (1981–2004)	
			GCV (% from LPA)*2	CC (*R*)
Model 1	5	J1, J2, J3, J5 and J6	32.04	0.84
Model 2	4	J2, J3, J5 and J6	32.72	0.82
Model 3	6	J1, J2, J3, J4, J5 and J6	33.44	0.83
Model 4	4	J3, J4, J5 and J6	34.21	0.82
Model 5	5	J1, J3, J4, J5 and J6	34.88	0.81
Model 6	5	J2, J3, J4, J5 and J6	35.54	0.81
Model 7	4	J1, J3, J5 and J6	36.08	0.79
Model 8	3	J3, J5 and J6	36.31	0.79
Model 9	5	J1, J2, J3, J4 and J5	36.84	0.82
Model 10	4	J1, J2, J3 and J5	37.41	0.83
Model 11	3	J3, J4 and J5	37.70	0.77
Model 12	4	J2, J3, J4 and J5	38.28	0.78
Model 13	3	J2, J3 and J5	39.85	0.78

The models were selected from all possible MR models constructed using predictors of SET-II

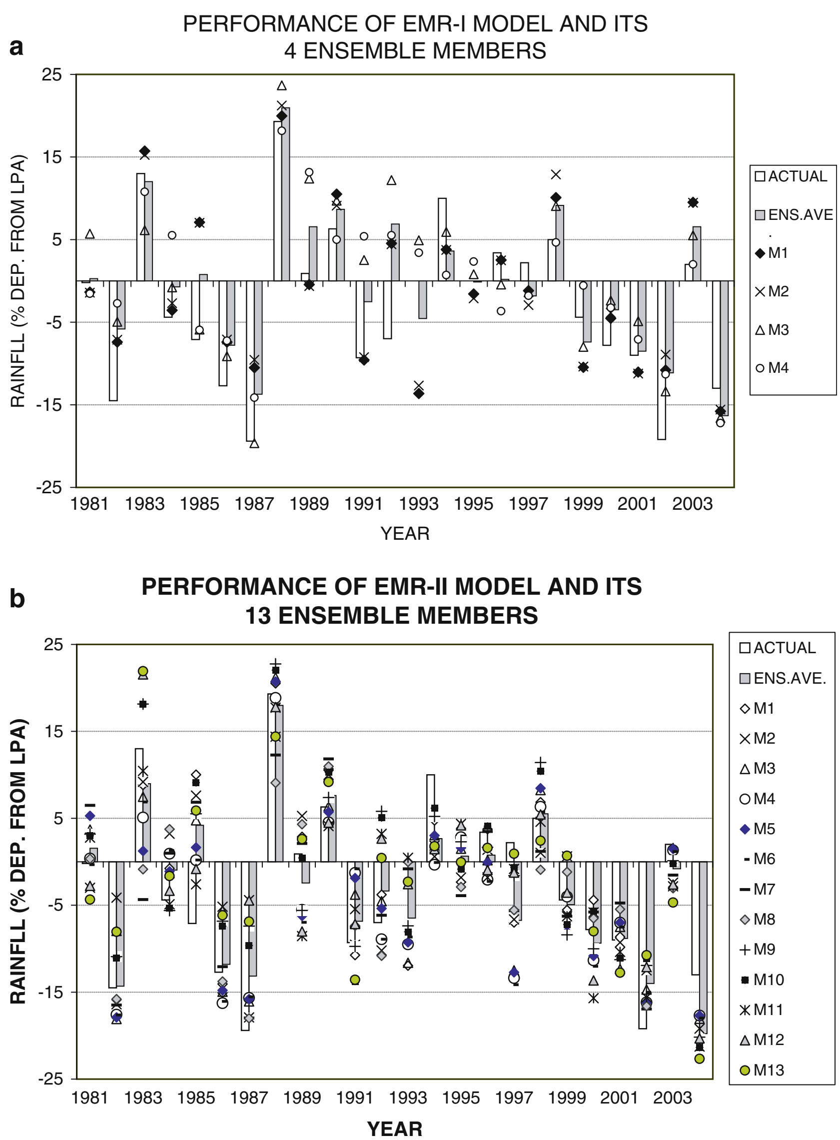


Fig. 6 **a** Performance of the forecasts of EMR-I model and its four ensemble members for the period (1981–2004) computed by sliding optimal training period of 23 years length. The *light* (*dark*)-*shaded bar* represents the actual (EMR-I forecast) ISMR. The forecasts from individual ensemble members are indicated using markers. **b** Same as **a**, but for performance of forecasts of EMR-II model and its 13 ensemble members for the period (1981–2004)

Table 6 Forecast verification statistics of the EMR and PPR models computed for the period 1981–2004

S. No	Verification parameter	EMR-I	EMR-II	PPR-I	PPR-II
1.	CC (*R*) between actual and predicted values	0.86	0.88	0.82	0.78
2.	BIAS of the forecasts (% from LPA)	2.4	–0.33	3.03	–0.92
3.	RMSE of the forecasts (% from LPA)	5.47	4.56	6.75	6.42
4.	HS (%)	67	75	63	58
5.	HSS	0.50	0.63	0.44	0.38
6.	FAR for below normal category (%)	0	0	0	11
7.	FAR for above normal category (%)	0	0	0	0
8.	POD below normal category (%)	100	100	86	67
9.	POD above normal category (%)	77	82	60	63

The last six verification parameters (4–9) are based on the three category forecasts where the predictand (ISMR) was categorized into three groups of equal prior probabilities. The three categories are below normal (<–7.45% from LPA), normal (–7.45–1.45% from LPA) and above normal (>1.45% from LPA)

period of 1968–1980) for forecasting ISMR in 1981 are depicted in Fig. 7a, b. Thus, the first two most interesting projections of the predictor set represented the linear and nonlinear relationships, respectively, between the ISMR and the predictors.

The year-to-year performance of the PPR models is given in Fig. 8. As seen, both the models were successful in predicting the ISMR during most of the years and particularly during the extreme years. However, the PPR-I model failed to predict the sign of ISMR correctly in four normal monsoon years (1981, 1992, 1996 and 1999). Similarly, the PPR-II model failed to correctly predict the sign of ISMR in three normal monsoon years (1985, 1990 and 1996). During the year 1993 (ISMR=0), the sign of the forecasts from both models was negative. On the other hand, during 1995 (ISMR=0), the sign of the forecasts was positive. Like the EMR models, the forecasts by the PPR models were all correct during the recent years.

The model verification statistics of the PPR models given in Table 6 shows that the RMSEs of the models

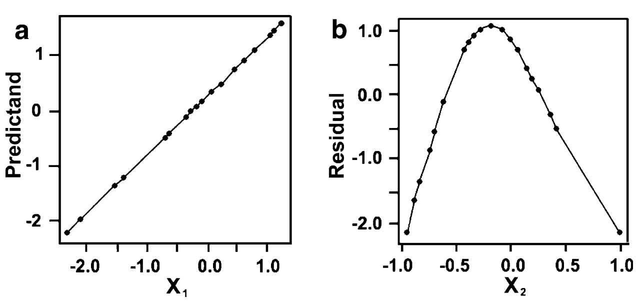


Fig. 7 **a** The *line plot* between the predictand (ISMR) and the first projection predictor ($\mathbf{X}_1 = \alpha_1^{\mathrm{T}}\mathbf{Z}$) and **b** the *line plot* between the residual $r(z) = \mathbf{Y} - f_1(\alpha_1^{\mathrm{T}}\mathbf{Z})$ obtained after removing the contribution of $\mathbf{X}_1$ in the ISMR and the second projection predictor ($\mathbf{X}_2 = \alpha_2^{\mathrm{T}}\mathbf{Z}$) during the period (1968–1980) used for training PPR-I model for the forecasting of ISMR of 1981

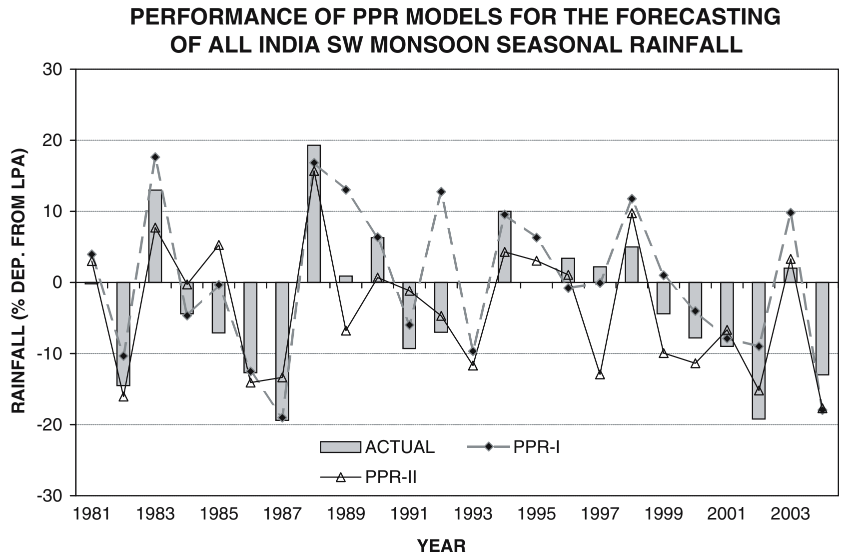
PPR-I and PPR-II for the period of 1981–2004 were 6.75 and 6.42% LPA, respectively. They were smaller than that of the forecasts based on climatology alone but were higher than that of the EMR models. The HSS of PPR-I and PPR-II models (0.44 and 0.38, respectively) were smaller than that of the EMR models. The FARs for below normal category by PPR-I and II models were 0 and 11%. But both of these models did not cause any false alarm for the above normal category. Probability for detecting below normal and above normal categories by PPR-I was, respectively, 86 and 67%. Probability for detecting for both the cases by the PPR-II model was around 60%.

6 Summary and conclusions

Because of the inherent problems in the statistical models such as epochal variation in the predictand–predictor relationship, inter-correlation between the predictors, changing predictability, etc., there is the necessity of subjecting statistical models to constant scrutiny and changes if necessary (Rajeevan et al. 2004). The changes can be brought out in different ways, such as changing the model size, the use of new predictors, changing the combination of the predictors, changing the length of model training period, etc. The changes are acceptable when the modified model shows better performance compared to the existing model during a common test period. The continuing efforts toward this end and attempts to adopt better statistical techniques have resulted in the development of new models that make use of novel statistical ideas for the forecasting of seasonal ISMR over the country as a whole.

Two models, namely EMR-I, and PPR-I, which are based on a predictor set (SET-I) needing data up to

Fig. 8 Performance of PPR models for the period (1981–2004) computed by sliding optimal training period of 23 years length. Actual rainfall is shown as *vertical bars*. Forecasts from PPR-I and PPR-II models are shown using *line plots*



March were developed to support the first stage forecast issued in April. Another two models namely EMR-II and PPR-II based on another data set (SET-II) requiring data up to May were developed to support the second stage forecast issued in June. The RMSE during the independent forecast period for all the models (4.56–6.75% from LPA) was relatively smaller than that for the model based on climatology alone (10% from LPA). All the models showed better skill (compared to the climatology-based model) in forecasting the ISMR during most of the years correctly. Particularly, during the extreme ISMR years, the predicted ISMR was close to the actual value. These models were also able to forecast the recent two deficient monsoon years (2002 and 2004) correctly. However, it is to be noted that the overall performance of the EMR models was better than the PPR models. Among the EMR models, the performance of the EMR-II was better than the EMR-I. While, the PPR-I performed slightly better than the PPR-II model.

This is the first time that the ensemble technique was applied in statistical models for predicting ISMR. The use of a weighted ensemble average of a set of suitable selected models with different predictor combinations for the model inferences effectively reduces the error resulting from the use of only a single best model. However, the reduction of error by the combined use of a set (ensemble) of models in place of a single model only reduces the chance of failure. There is no guarantee of correct forecasts in all the occasions. Here, we have used a set of MR models with least RMSEs among all possible MR models for the ensemble forecast. Other techniques such as neural network, PPR, etc. may also be used in place of the MR technique for developing ensemble models. We have attempted such experiments and found that there are not many significant changes from the results that we have presented here.

The PPR is a new nonparametric technique, used for the first time in the forecasting of the ISMR. In this method, the ISMR was expressed as the sum of two parts. The first part was computed from the first most interesting projection that showed a linear relationship with the predictand. The second part was computed from the second most interesting projection that showed a nonlinear relationship with the residual obtained by removing the contribution of the first projection from the ISMR. Iyengar and Ragukanth (2003) suggested a method of separating the ISMR series into linear and nonlinear parts using a decomposition technique and then predicting them individually. But their method used the time series of the ISMR itself only for this purpose and did not use any predictor parameters. In the PPR method, the predictors (derived from slowing varying boundary conditions) that had significant physical and statistical relationships with ISMR were used to predict the linear and nonlinear parts of the ISMR. Thus the PPR model is conceptually better placed to take into account the real nonlinear relationship that may exist between the predictors and the rainfall while making a forecast.

It is interesting to note that we have used some predictors from Europe and Atlantic Ocean for the development of LRF models. This is due to the improved statistical relationship of ISMR with the Atlantic and Europe climate anomalies during the recent years (Rajeevan 2002). Recent studies (Gadgil et al. 2003, 2004) have shown the influence of the equatorial Indian Ocean on the variability of ISMR. We need to explore precursors for the events in the equatorial Indian Ocean (like EQUINOO) to use as predictors in the empirical models along with other ENSO-related and European and Atlantic predictors.

Various components of the Indian monsoon exhibit significant inter-decadal variability (see the references given in Goswami 2005). Modulation of inter-annual variability by the inter-decadal variability is also reflected in the epochal/secular variation of the predictor–predictand relationship that influences predictability of the seasonal mean monsoon (Goswami 2005). A recent study by Goswami (2004) revealed that potential predictability of monthly mean summer monsoon climate has decreased by almost a factor of two during the recent decades (1980s and 1990s) compared to the decades of 1950s and 1960s associated with the major inter-decadal transition of climate in mid 1970s. We feel that the constant updating of the models (as done in this study) using the sliding training period method with an optimal window period can offset the effect of variation to some extend in the predictor–predictand relationship (see Fig. 2) and improve the predictability. In this study, we found that the optimal length of training period is 23 years. The sliding training method has better predictive skill over the traditional method in which the model is trained using the first few years and forecasts are computed for the remaining years using the same model constants. To prove this point, we developed a MR model using all of the six predictors of SET-I. The model was trained using data for the period of 1958–1995 and forecasts were computed for the remaining years. We found that the forecast errors of the MR model trained using a longer period were generally more than that compared to the EMR-I model. More importantly, the model trained with fixed training period (1958–1995) was not able to correctly forecast the recent drought years (2002 and 2004).

In order to examine the performance of the EMR and PPR models operationally, we had prepared the forecasts for 2005 just prior to the 2005 SW monsoon season. Preliminary forecasts from these new experimental models were included in the official press releases made by IMD on the LRF for the 2005 southwest monsoon rainfall (http://www.imd.ernet.in). The forecasts for the 2005 SW monsoons seasonal rainfall over the country as a whole by EMR-I and PPR-I models were, respectively, 4 and 1% from LPA and that by EMR-II and PPR-II models were, respectively, 1 and 7% from LPA, respectively. The realized rainfall in 2005 season was -1% from LPA indicating that the forecasts from these models were closer to the realized rainfall. We have now prepared experimental forecasts for the 2006 monsoon season. The forecasts for 2006 by the EMR-I and PPR-I model are -5 and -11% from LPA, respectively. The forecasts for 2006 by the EMR-II and PPR-II models are -7 and -6% from LPA, respectively.

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