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Hydroclimatic association of the monthly summer monsoon rainfall over India with large-scale atmospheric circulations from tropical Pacific Ocean and the Indian Ocean region

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Abstract

The hydroclimatic association between the monthly Indian summer monsoon rainfall and a proposed monthly composite index (MCI) of large-scale atmospheric circulations from the Pacific Ocean and Indian Ocean regions is established. The spatial variability of this association is also checked. The predictability of the monthly Indian summer monsoon rainfall using the MCI is also investigated and is seen to be encouraging. Copyright © 2006 Royal Meteorological Society

Keywords: **El Niño-Southern oscillation; Equatorial Indian Ocean oscillation; Indian summer monsoon rainfall; hydroclimatic association; uncertainty; probabilistic prediction**

1. Introduction

The assessment of the hydroclimatic association between spacio-temporal variation of rainfall and different large-scale atmospheric circulations is very important for the socio-economic benefit of a country. Some work has been done to explore the statistical relationship between hydrologic variables like rainfall, streamflows etc. and large-scale climate indices in the United States (Kahya and Dracup, 1993; Jain and Lall, 2001), Australia (Verdon *et al*., 2004), New Zealand (McKerchar *et al*., 1998) and other countries. A significant influence of the El Niño-Southern oscillation (ENSO) on rainfall has been established globally, including in India (Rasmusson and Carpenter, 1983; Ropelewski and Halpert, 1987; Kawamura *et al*., 2004). The hydroclimatic teleconnection between the Indian summer monsoon rainfall (ISMR) and ENSO events through the coupled oceanic–atmospheric phenomenon has been explained in literature (Rasmusson and Carpenter, 1983). According to Krishna Kumar *et al*. (1999), during the El Niño event, the rising limb of the Walker circulation shifts towards the central or eastern part of the tropical Pacific Ocean and an anomalous subsidence exists over the Indian subcontinent. This subsidence, suppressing the convection and the precipitation over the Indian region, results in a lower-than-normal rainfall. However, in recent years, some inconsistent observations suggest that the interdecadal variability of the ISMR is much more complex (Krishnamurthy and Goswami, 2000; Chang *et al*., 2001). The recent discovery of the Indian Ocean Dipole (IOD) mode and its impact on the ISMR is a major advancement (Saji *et al*., 1999; Webster *et al*., 1999; Ashok *et al*., 2001) in this field.

The Equatorial Indian Ocean oscillation (EQUINOO) is the atmospheric part of the IOD mode. The physical mechanism behind the link between the ISMR and EQUINOO is due to the association of large-scale monsoon rainfall over the Indian region with the northward propagation of the convective system generated over the Indian Ocean region (Gadgil *et al*., 2004).

As both the ENSO and EQUINOO have their impact on the ISMR, ENSO (EQUINOO) may assist or hinder the effect of EQUINOO (ENSO). Therefore, it is logical to investigate their joint influence on the ISMR in terms of some composite index.

Gadgil *et al*. (2004) have shown an association of the seasonal ISMR with a linearly combined index between seasonally averaged ENSO and EQUINOO. However, both these indices and the ISMR were averaged over the same period of each year (June to September). Hence, both these climate indices need to be predicted first. A composite index, derived from these predicted indices, can then be used as a precursor of the total monsoon rainfall. The use of such predicted indices increases the uncertainty in prediction. Also, Gadgil *et al*. (2004) did not consider any lagged relationship between the ISMR and the composite index of ENSO and EQUINOO. Moreover, they have considered the total monsoon rainfall (June to September) in their study.

In the field of water resources management, monthly rainfall values are more useful than the total rainfall for the entire monsoon period for planning cropping operations, reservoir operations, allocation of water to different users etc. In a recent study, it has been established that a significant influence of both ENSO and EQUINOO on the ISMR at monthly time-scale exists (Maity and Nagesh Kumar, 2006), considering the two indices separately. Separate information on both these indices allows the investigation of their relative influence, as detailed in the study. However, combining the information in these indices before using it in the model is advantageous in many ways. For example, it helps in investigating the association between the combined index and the ISMR. Another important point is that, once the association between the combined index and the ISMR is established, the combined index can be used in any modeling approach, instead of using the two indices separately. As a consequence, the number of model parameters gets reduced. Thus, in this study, the information on ENSO and EQUINOO is combined through a monthly composite index (MCI) and the hydroclimatic association between the monthly variation of the ISMR and the MCI, considering the lagged relationship, is investigated. The spatial variability of this association is also investigated for different homogeneous monsoon regions in India. The MCI for monsoon months has been developed on the basis of the lagged relationship between the monthly ISMR and the corresponding indices of ENSO and EQUINOO. The predictive potential of the MCI for the monthly variation of the ISMR is investigated using the Bayesian dynamic linear model (BDLM). This model is able to capture the uncertainty associated with the predictions, which is very useful in many fields of interest (West and Harrison, 1997; Berliner *et al.*, 2000; Maity and Nagesh Kumar, 2006).

2. Data

The sea surface temperature (SST) anomaly, from Niño 3.4 region (5°S – 5°N, 120° – 170°W), is used as the 'ENSO index'. Monthly SST data for the period January 1958 to December 2003 are obtained from the website of the National Weather Service, Climate Prediction Centre of National Oceanic & Atmospheric Administration (NOAA).

Monthly surface wind data for the period January 1958 to December 2003 are obtained from the National Center for Environmental Prediction. The negative of the zonal wind anomaly over the equatorial Indian Ocean region (60° – 90°E, 2.5°S – 2.5°N) is used as the 'EQUINOO index' (Gadgil *et al.*, 2004).

Monthly rainfall data (Parthasarathy *et al.*, 1995) for 'all India' and five different 'homogeneous monsoon regions' (refer Figure 4 for their locations) are obtained for the period January 1958 to December 2003 from the website of the Indian Institute of Tropical Meteorology, Pune, India. Standardised monthly anomaly values, for the above data sets, are used in the present study.

3. Relationship of 'all India' rainfall with the ENSO and EQUINOO indices

Cross-correlation coefficients are computed between the monthly rainfall anomaly for each monsoon month and the circulation indices considering different lags and lead times. Results are plotted in Figures 1 and 2 for the ENSO and EQUINOO index respectively. In general, correlation coefficients are statistically significant for a few months and insignificant for others (the significant correlation coefficient is 0.29 at 95% confidence level).

However, it is also observed that, for all the monsoon months, the maximum correlated EQUINOO index is always from some preceding month, which is therefore most useful in prediction. But the maximum correlated ENSO index is always from some

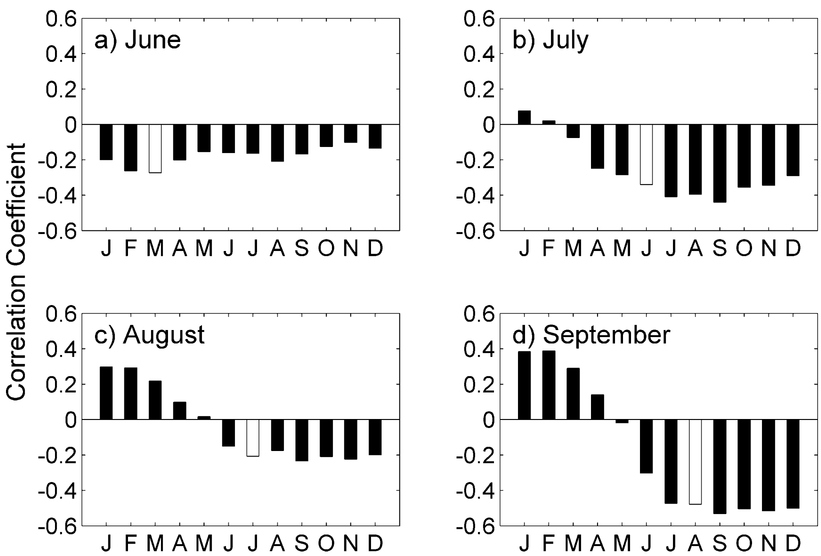

Figure 1. Plots of correlation coefficients between the ENSO index and the standardised monthly rainfall anomaly for (a) June, (b) July, (c) August and (d) September. The unfilled bar in each panel denotes the month used for the MCI

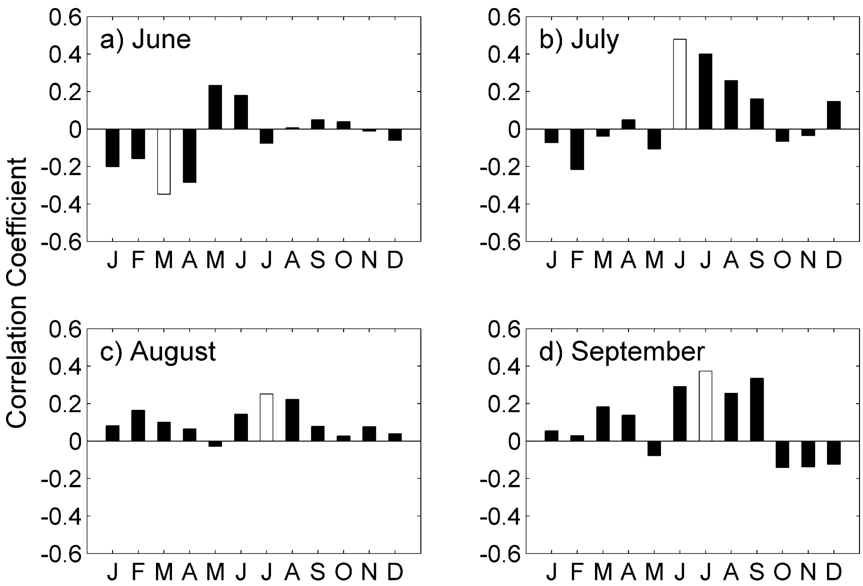

Figure 2. Plots of correlation coefficients between the EQUINOO index and the standardised monthly rainfall anomaly for (a) June, (b) July, (c) August and (d) September. The unfilled bar in each panel denotes the month used for the MCI

succeeding month, except for June rainfall. To incorporate both these phenomena, two different approaches can be followed. The ENSO index can be predicted by the coupled ocean–atmosphere model and this predicted index can be utilised. Or, the maximum correlated preceding month of the ENSO index can be ascertained and information from that month can be utilised. In the first approach, uncertainty is associated with the predicted ENSO index, which adversely affects the prediction performance of rainfall. In the second case, the correlation coefficient for the maximum correlated preceding month is slightly less than the overall maximum correlation coefficient among all months. However, from Figure 1, it may be noticed that the correlation coefficient of the best preceding month does not differ considerably from the overall maximum correlation coefficient. A major advantage of the second approach is that, instead of using the predicted ENSO index, the observed ENSO index can be used, which, in turn, will reduce the uncertainty in rainfall prediction. Hence, in this study, the second approach is followed. It can be concluded from the above analysis that, for June rainfall, both ENSO and EQUINOO indices from March; for July rainfall, both ENSO and EQUINOO indices from June; for August rainfall, both ENSO and EQUINOO indices from July and for September rainfall, the ENSO index from August and the EQUINOO index from July are the best correlated. These months are highlighted in Figures 1 and 2 as unfilled bars.

4. Monthly Composite Index (MCI)

Having identified the best correlated preceding month of circulation indices, the MCI has been developed to explore its association with the monthly variation of the ISMR. The ENSO and EQUINOO indices are linearly combined to obtain the MCI. Thus,

$$MCI = \alpha \, . \, EN + \beta \, . \, EQ \tag{1}$$

Here EN stands for the ENSO index and EQ stands for the EQUINOO index. Linear combinations, for the four monsoon months, are achieved by the least-square technique. Equations for MCI, thus obtained for the four monsoon months, are shown in Table I.

However, many researchers have pointed out a significant interdecadal change in the relationship between the ISMR and the large-scale circulation

Table I. Details of the monthly composite index (MCI) and the correlation coefficients between the monthly rainfall anomaly and the MCI

Month of rainfall anomaly	Month of ENSO information	Month of EQUINOO information	Equation for the MCI	Correlation coefficient[a]
Jun	Mar	Mar	$MCI = -0.18^{*}NINO_{Mar} - 0.29^{*}EQWIN_{Mar}$	0.38
Jul	Jun	Jun	$MCI = -0.24^{*}NINO_{Jun} + 0.43^{*}EQWIN_{Jun}$	0.54
Aug	Jul	Jul	$MCI = -0.24^{*}NINO_{Jul} + 0.28^{*}EQWIN_{Jul}$	0.35
Sep	Aug	Jul	$MCI = -0.53^{*}NINO_{Aug} + 0.44^{*}EQWIN_{Jul}$	0.65

[a] Significant correlation coefficient is 0.29 at 95% confidence level.

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phenomena (Krishna Kumar *et al.*, 1999; Torrence and Webster, 1999). Thus, such a linear combination may be subject to an interdecadal change. Hence, the robustness of the equations for the MCI is investigated. First, an optimal data length is selected, which should be short enough to reflect the variability associated with climate change and long enough to average out the short-term fluctuations. To investigate this optimal data length, coefficients of equations for the MCI are obtained for varied length of data, from 8 years to 46 years. It is observed that, when the data period becomes longer than 35 years, the coefficients become more or less stable with very little variability. Next, a sliding window of 35 years is used for calculation of different coefficients for the equations of the MCI. It is observed that coefficients are more or less stable with very little variation. This information is used later for independent verification of predictions.

5. Association of the monthly ISMR with the MCI and spatial variability

Correlation coefficients between the MCI and the monthly rainfall anomaly are shown in Table I for all the monsoon months. It is observed that all the correlation coefficients are statistically significant (the significant correlation coefficient being 0.29 at 95% confidence level). Also, they are higher than the correlation coefficients between the rainfall anomaly and either the ENSO index or the EQUINOO index. It is worthwhile to note that the ENSO and EQUINOO indices are independent (Saji *et al.*, 1999), and the correlation coefficient between the 'ENSO index' and the 'EQUINOO index', which was used to obtain the MCI for monsoon months, is statistically very insignificant (0.091).

It is beneficial to investigate how much extra variability is explained by the MCI. Scatter plots between standardised monthly rainfall anomaly and (a) the MCI, (b) the ENSO Index and (c) the EQUINOO index for all monsoon months are plotted in Figure 3. A correlation coefficient of 0.50 (>0.14 is significant at 95%) is obtained between the monthly rainfall anomaly and the MCI, i.e. 25% of variability of the monthly ISMR is associated with the MCI. However, while considering only ENSO information and only EQUINOO information, it is observed that 11% of variability of monthly monsoon rainfall is associated with only ENSO information and 4% with only EQUINOO information (Figure 3).

The spatial variation of the association of the MCI is investigated for five different homogeneous monsoon regions of India (Figure 4). It is observed that the association of the monthly rainfall variation with the MCI is much better than that with either ENSO or EQUINOO when considered alone for all five different homogeneous monsoon regions. However, it is also observed that the MCI is significantly associated with the monthly rainfall variation for north-west

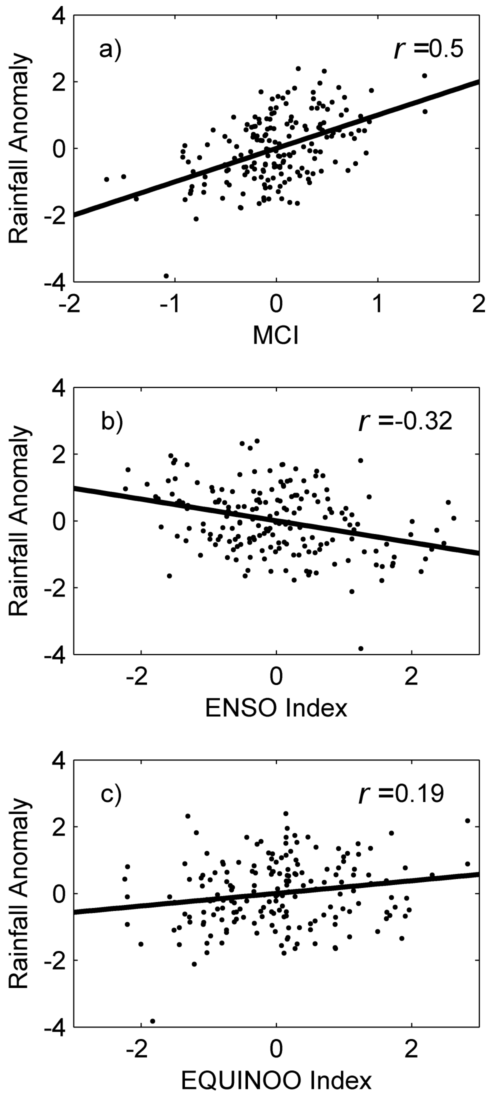

Figure 3. Scatter plot between standardised monthly rainfall anomaly and (a) the monthly composite index (MCI), (b) the El Niño-Southern oscillation (ENSO) index and (c) the Equatorial Indian Ocean oscillation (EQUINOO) index for all monsoon months

(NW), central north-east (CNE), west-central (WC) and peninsular (PE) India (correlation coefficients are in the order of 0.40) but, in case of north-east India, this correlation coefficient is very low (0.17). Thus, the association of the MCI with monthly rainfall variation for north-east India is not strong, but is well associated for other parts of India. It may be noted that the phase relationship of rainfall with ENSO and EQUINOO may have a little perturbation for different homogeneous monsoon regions. However, the above analysis is presented considering the same phase of the relationship as that of all Indian rainfall with ENSO and EQUINOO.

6. Predictive potential of the MCI for the monthly ISMR using the BDLM

The BDLM is used to investigate the predictive potential of the MCI for the monthly ISMR. The

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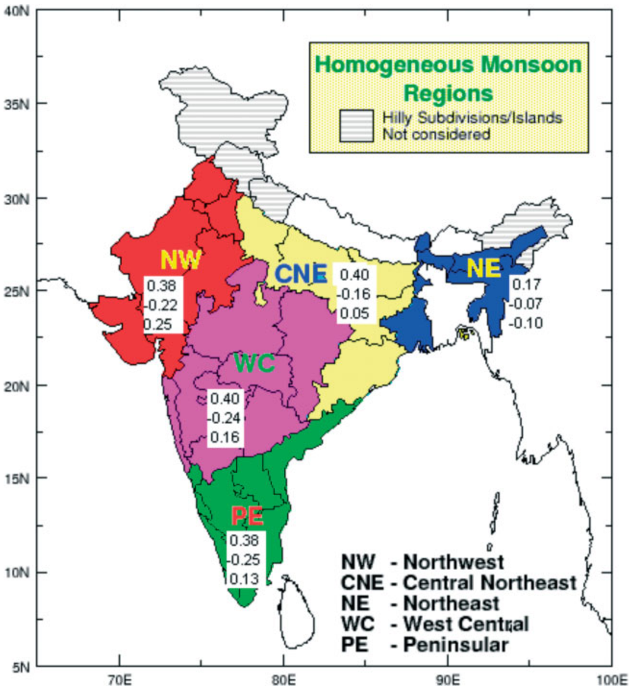

Figure 4. Spatial variation of the association between the MCI with rainfall over different homogeneous monsoon regions. Three different correlation coefficients are shown for each region in a vertical sequence. These are between the monthly rainfall anomaly during monsoon months and (1) the MCI, (2) the ENSO index and (3) the EQUINOO index, respectively

superiority and usefulness of the BDLM for the present problem is briefly described here. Independent verification of predictions is examined by using a part of the data for model calibration and the rest for performance checking.

In many linear and non-linear approaches, though the prediction performance is satisfactory, there is no means to account for the uncertainty associated with the predictions. However, the problem in rainfall prediction is associated with high uncertainty, which must be addressed to the extent possible. The BDLM provides information on the uncertainty associated with prediction, which is very useful for the end users. It provides the uncertain future values as a distributional form. Such models also allow incorporation of exogenous inputs. Thus, information of the MCI can be incorporated in the model to predict the monthly rainfall. The BDLM updates its parameters at each time step due to its dynamic property. Thus, this kind of a model is more suitable for capturing the slow-moving time-varying relationship between the two time series having a cause–effect relationship. The stationarity assumption can be relaxed for this model, which is also a very useful property for the problem addressed in this study. Another important point is that, as the model provides the uncertain future rainfall values as a distributional form, computation of the confidence interval for the forecasted values is possible, which is advantageous in many application fields. The Artificial Neural Network (ANN) is a popular prediction technique that can capture the non-linear relationship between the two time series. However, in the ANN approach, there is no means to account for the uncertainty associated with predictions, whereas the BDLM provides complete information on the uncertainty associated with prediction by producing the predictions as a distributional form, which is more helpful in statistical decision-making.

A brief description of the BDLM for the monthly ISMR using the MCI as an exogenous input is presented here. The observation equation is $RA_t = \theta_t \, mci_t + \nu_t$, where RA_t is the observed anomaly value of the monthly ISMR series at the tth time step; mci_t is the value of the MCI for the tth time step; θ_t is the regression parameter at the tth time step and ν_t is the normally distributed observational error at the tth time step with mean 0 and unknown variance V, i.e. $\nu_t \sim N[0, V]$. The assumption of normality is tested by plotting a normal probability plot and a histogram superimposed with a normal curve. The regression parameter θ_t is updated sequentially by the system of equations at each time step using system equation: $\theta_t = \theta_{t-1} + \omega_t$, where ω_t is the Student-T distributed system evolution error with degree of freedom n, at the tth time step with parameter 0 and W_t, i.e. $\omega_t \sim T_n[0, W_t]$, where n is numerically equal to the time step t. Model parameters are updated at each time step to obtain a one-step-ahead forecast and posterior distribution for the next time step. Details of the modeling approach and related mathematical proof are given in West and Harrison (1997) and its application to the atmospheric field can be found elsewhere (Berliner *et al.*, 2000; Maity and Nagesh Kumar, 2006).

The BDLM is used to predict the monthly rainfall with the MCI as the exogenous input. As described in Section 4, the data period of 35 years results in a stable equation for the MCI. The model is calibrated for the period 1958–1992 and tested for the period 1993–2003. Results are shown in Figure 5 for the model-testing period. A 90% confidence interval of the predictions is also shown. It can be seen that observations are well captured by the prediction confidence interval except for July 2002 (in July 2002, the observed rainfall was glaringly exceptional, being 49% lower than normal). In general, the observed and predicted monthly rainfall values are in good agreement with a correlation coefficient of 0.78.

It can be mentioned that, in the years 1997 and 2002, the negative correlation between ENSO and the ISMR is not well reflected. In 1997, a drought was expected due to the century record El Niño. However, the summer monsoon rainfall was slightly above normal in 1997. In 2002, a severe drought was not expected as it was, even if there were a mild El Niño. The reason was investigated and a joint influence of ENSO and EQUINOO was suspected (Gadgil *et al.*, 2004). It can be observed from Figure 5 that the normal rainfall in 1997 was successfully predicted by the BDLM using the MCI. In 2002, the overall low rainfall during all monsoon months was predicted, even though the

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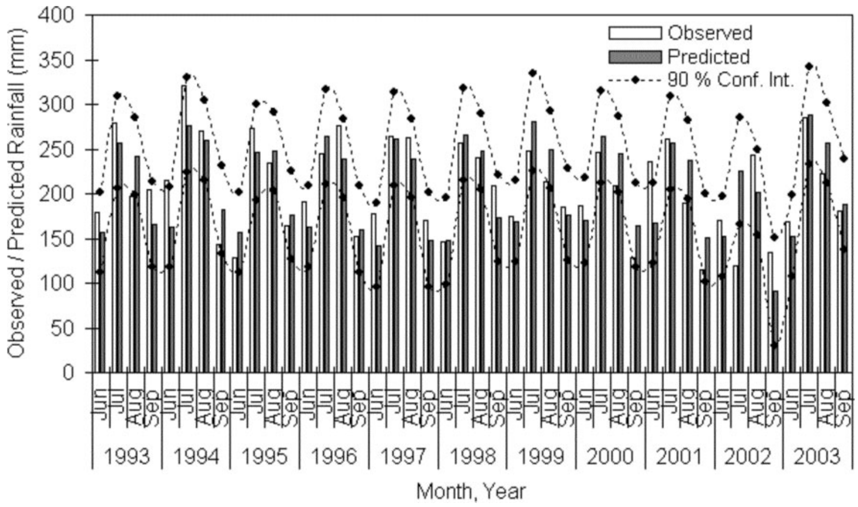

Figure 5. Prediction performance of Bayesian dynamic linear model using the information of monthly composite index (MCI) as exogenous input

exceptionally low (49% below normal) rainfall in July 2002 was not predicted well. Exceptionally low (49% below normal) rainfall in July 2002 may have been due to some other reason. In general, the BDLM is able to successfully predict the monthly rainfall variation using the information of the MCI. The successful prediction of the monthly rainfall using the MCI is due to the dynamic property of the model that helps capturing the dynamic relationship between the monthly rainfall and the MCI. Thus, the BDLM is able to get more information out of the MCI than a simple linear regression, which indicates the usefulness of the BDLM. Another important point is related to the uncertainty quantification by producing the predictions as a distributional form, which helps estimate any desired statistical confidence interval of the predicted values. In Figure 5, a 90% confidence interval of the predictions is plotted, which is shown to capture the observations with reasonable accuracy.

It is worthwhile to note here that when the ENSO index and the EQUINOO index were used individually, the performance of the model was poorer in both the cases compared to that using the MCI. Specifically, while using the ENSO index and the EQUINOO index individually, the correlation coefficients between the observed and the predicted monthly rainfall values during the model testing period were respectively 0.71 and 0.72, as against 0.78 while using the MCI. This was due to the fact that the association between the MCI and the ISMR was higher than that between the ENSO index and the ISMR as well as the EQUINOO index and the ISMR, as discussed earlier.

7. Conclusions

In this study, a significant association between the monthly ISMR and the MCI is established. It is observed that 25% of total variability of all India monthly rainfall in monsoon months can be explained by the MCI as against 11% with only ENSO information and 4% with only EQUINOO information. However, the association is not spatially uniform – it is poor for North-east India and stronger for other homogeneous monsoon regions of India. Finally, conspicuous predictive potential of the MCI for the monthly ISMR is observed through the BDLM, which can be used to predict the monthly ISMR along with the associated uncertainty in prediction, using the information of the MCI.

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