Hybrid (dynamical–empirical) forecast of Indian monsoon rainfall during 2016

The variability of all-India summer monsoon rainfall (AISMR) during June to September (JJAS) has immense impact on various sectors, including agriculture, water resource, power, etc. in the country. Majority of cropped area in India (about 57%) is rainfed and coincides with the region of medium and low range of monsoonal rainfall. As a result, it is affected by the vagaries of the southwest monsoon. Thus for an agro-economic country like India, prediction of AISMR in advance is vital for policy planning and the economy. H. F. Blanford was the first to predict the prospective monsoon rainfall over India by utilizing snowfall over the Himalaya during the preceding winter and spring seasons[1]. Since then, the seasonal prediction of AISMR has passed through several milestones and during the last few decades, many empirical models have been developed[2–5] with varying degree of success. On the other hand, over the period of the last 10–15 years the dynamical prediction has evolved with many seasonal climate prediction centres using coupled general circulation models (CGCMs) for routine seasonal climate prediction. However, as indicated by some studies[6–8], the skill of the monsoon prediction by the dynamical models was poor until 2005. Subsequently, there have been significant improvements in the skill of the dynamical models[9–11]. Although the CGCMs have been improved, real-time prediction of the Indian monsoon using such models remains a challenging task. Furthermore, as demonstrated by some recent studies, the skill of coupled models in predicting large-scale variables is comparatively better compared to that of Indian monsoon rainfall[7,12,13]. Congwen *et al.*[12], using the variability of the 500 hPa geopotential height (GPH) for the downscaling of summer monsoon precipitation anomaly could get higher forecast skill corresponding to the conventional forecast. Pattanaik and Kumar[7,13] have also shown that the actual forecast skill of AISMR by coupled models can be further improved using the hybrid concept (dynamical–empirical model), developed based on forecast variables from the models having significant correlation with AISMR. The reason for exploring hybrid forecast of Indian monsoon rainfall is because rainfall being a localized process, it is much harder to predict and large-scale circulation can be relatively easier to predict.

The second version of the NCEP CFS (CFSv2) coupled model was made operational at National Centre for Environment Prediction (NCEP) during March 2011 (ref. 14). The atmospheric component of this model has a spectral triangular truncation with 126 waves (T126) in the horizontal and 64 hybrid layers in the vertical compared to CFSv1, which has triangular truncation of 62 waves (T62). In CFSv2, the ocean model has changed from MOMv3 to MOMv4 with the domain changed from a quasi-global domain (75°S to 65°N) to a fully global one along with a change in resolution. One major component of CFSv2 was to have a coupled atmosphere–ocean–sea ice-land reanalysis from 1979 to 2011 with the new system (Climate Forecast System Reanalysis, CFSR) at NCEP for the purpose of generating initial conditions for CFSv2 retrospective forecasts for the period from 1982 to 2009. The spatial patterns of JJAS mean rainfall and its interannual variability were more realistic over the Indian monsoon region in CFSv2 compared to that in CFSv1 (ref. 13). Although the CFSv2 coupled model shows more realistic teleconnection patterns between El Niño and Indian summer monsoon rainfall, the Niño3.4 forecast sea surface temperature (SST) from CFSv2 as predictor in the regression model did not yield much improvement in the prediction of AISMR. The correlation coefficients (CCs) between observed and predicted AISMR with Niño3.4 forecast SST from CFSv2 as predictor with March, April and May ensembles were found to be 0.47, 0.48 and 0.40 respectively, during the whole hindcast period of 28 years, compared to the raw CCs (0.40, 0.48 and 0.47 respectively) of CFSv2 for the same period. So, a new hybrid (dynamical–empirical) model based on the forecast variables of CFSv2 by using other forecast variables (other than El Niño index) was developed[13]. These authors[13] used three indices based on the region of significant CCs during the training period from 1982 to 2004 in the hybrid model after analysing many forecast variables from NCEP CFSv2 valid for JJAS based on March ensembles. These are: (i) the forecast geopotential height averaged over 157.5°–172.5°E; 30°–40°N; known as *Z*850-index, (ii) the forecast rainfall averaged over 70°–50°W; 50°–40°S; known as *R*-index, and (iii) 850 hPa zonal wind averaged over 65°–50°W;

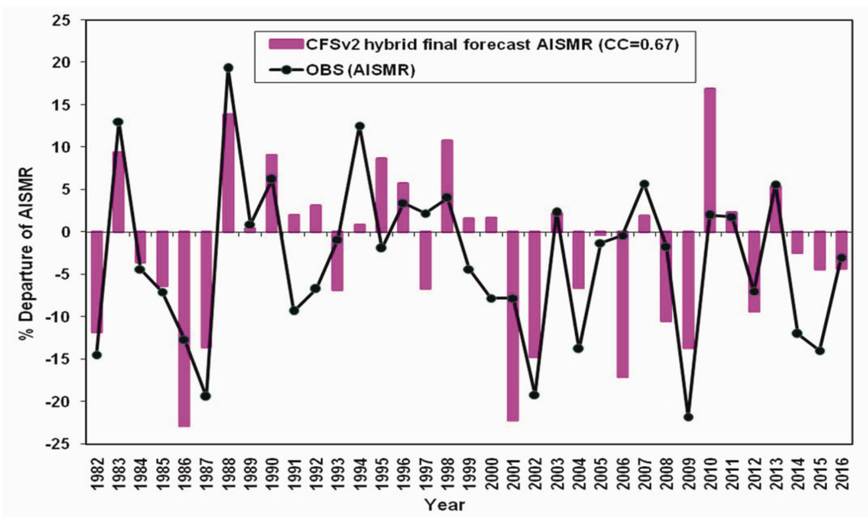

Figure 1. The variance inflated/deflated final forecast of All India Summer Monsoon Rainfall (AISMR) based on the hybrid model of CFSv2 forecast variables of March ensembles for the whole period of 35 years (1982–2016).

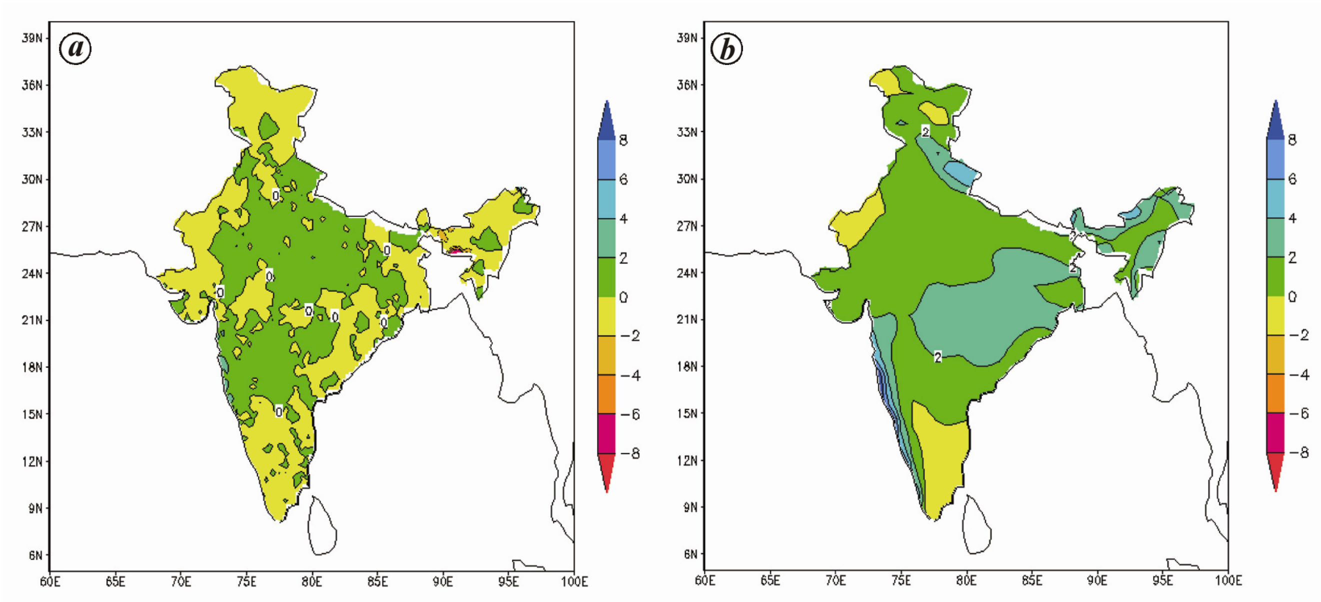

Figure 2. ***a***, Observed rainfall anomaly (mm/day) during June to September, 2016. ***b***, CFSv2 forecast rainfall anomaly during June to September 2016 based on the initial condition of March.

Table 1. Contigency table showing the performance of AISMR forecast during the whole period of 35 years (1982–2016) and 12 years test period (2005–2016)

Observed AISMR categories whole period; 1982–2016 (Test period; 2005–2016)	Number of categories based on forecast AISMR departure Whole period 35 years; 1982–2016 (test period 12 years; 2005–2016)		
	Excess (E)	Normal (N)	Deficient (D)
E-03 (00)	01 (00)	02 (00)	00 (00)
N-24 (09)	02 (01)	19 (06)	03 (02)
D-08 (03)	00 (00)	03 (02)	05 (01)
Total 35 (12)	03 (01)	24 (08)	08 (03)

67°–71°N; known as $U850$-index, having significant CC with the observed AISMR. The linear prediction of AISMR based on these three indices of CFSv2 is

$$\mathrm{AISMR}_{Z850\text{-index}} = 1.47{*}Z_{850} - 2231.04,$$

$$\mathrm{AISMR}_{R\text{-index}} = -72.54{*}R + 120.48,$$

$$\mathrm{AISMR}_{U850\text{-index}} = 70.13{*}U_{850} - 21.71,$$

$$\mathrm{AISMR}_{\mathrm{mean}} = (\mathrm{AISMR}_{Z850\text{-index}} + \mathrm{AISMR}_{R\text{-index}} + \mathrm{AISMR}_{U850\text{-index}})/3. \quad (1)$$

By taking the average of AISMR forecasts based on the three linear regression models using the three indices, the mean hybrid forecast ($\mathrm{AISMR}_{\mathrm{mean}}$) was calculated. Then, the variance inflated/deflated final forecast of AISMR based on the hybrid model was calculated for the entire 28 years from 1982 to 2009 (first 23 years for the training period and the last 5 years for the test year). As shown by Pattanaik and Kumar[13], the forecast skill of this hybrid model in terms of CC was found to be much higher (CC = 0.69) than the raw forecast skill of the CFSv2 model (CC = 0.40) during the same period (1982–2009). Further, since data for seven more years, i.e. 2010 to 2016 were available, the final hybrid forecasts were also calculated during the recent test period.

As seen from Figure 1, the final hybrid forecast shows highly significant CC (0.67) during the whole period of 35 years with values during the 23 years training period (1982–2004) and 12 years test period (2005–2016) being 0.73 and 0.51 respectively. It is interesting to see from Figure 1 that all the 12 years during the test period correctly predict the sign of the AISMR departure and thus, the accuracy of capturing the sign correctly is 100% during the period. With respect to capturing the excess (E; AISMR departure ≥ 10%), normal (N; AISMR departure between –10% and +10%) and deficient (D; AISMR departure ≤ –10%) years in the forecast, a contingency table was prepared (Table 1). As seen from Table 1, the hybrid model performs well in capturing the observed category of three 'E' years as either 'E' or 'N' years and eight 'D' years as either 'D' or 'N' years. There are some false alarms also (about 19%), as 19 out of 24 'N' years are correctly predicted by the model, with the remaining five years indicated as two 'E' (1998 and 2010) and three 'D' (2001, 2006 and 2008) years.

The monsoon of 2016 was unique as after two consecutive drought years of 2014 and 2015, the observed AISMR during 2016 (Figure 2 *a*) was 3% less from its long period average (LPA). The El Niño conditions over equatorial Pacific Ocean that established in April 2015, reached a peak in December 2015 and subsequently started weakening, although above normal SST over the Pacific prevailed during March 2016. The statistics prepared from previous monsoon seasons over India indicated that 65% of the El Niño years were associated with deficient or below normal (<96% of LPA) AISMR years (http://www.imd.gov.in). However, during 71%

of the years followed by El Niño years, monsoon was expected to be normal to above normal (≥96% of LPA). Considering this analogy, the 2016 monsoon was also expected to be normal to above normal with a probability of 71%. On the other hand, the coupled model forecasts available in February and March 2016 also indicated moderate to weak El Niño during June–July and ENSO neutral conditions likely to get established thereafter (August–September). Considering this aspect, most of the statistical and dynamical models had indicated normal to above-normal rainfall for the 2016 southwest monsoon season. Consistent with this, real-time forecast based on the March ensembles of NCEP CFSv2 coupled model valid for 2016 JJAS also indicated stronger monsoon associated with above normal rainfall over most parts of India (Figure 2 *b*), with a quantitative value of 106% from its LPA. Thus, the real-time forecast from NCEP CFSv2 also indicated above-normal monsoon rainfall during JJAS 2016.

Based on the three indices (*Z*850-index, *R*-index and *U*850-index), the final variance inflated/deflated AISMR forecast for the 2016 southwest monsoon rainfall over India was found to be 96.1% of its LPA, which is very close to the observed AISMR of 97% of its LPA. The *Z*850-index, *R*-index and *U*850-index individually indicated AISMR departure for 2016 as +5.6%, –11.1% and –6.8% respectively. Thus, it is the combination of the three parameters that contributed to correct forecast of 2016. Hence the hybrid forecast developed by Pattanaik and Kumar[13] could capture the variability of AISMR for 2016 and correctly predicted the seasonal rainfall departure, when most of the statistical/dynamical models predicted rainfall to be on the positive side of the normal.

1. Blanford, H. F., *Proc. R. Soc London*, 1884, **37**, 3–22.
2. Shukla, J. and Mooley, D. A., *Mon. Weather Rev*., 1987, **115**, 695–703.
3. Gowariker, V., Thapliyal, V., Kulshrestha, S. M., Mandal, G. S., Sen Roy, N. and Sikka, D. R., *Mausam*, 1991, **42**, 125–130.
4. Sahai, A. K., Grimm, A. M., Satyan, V. and Pant, G. B., *Climate Dyn*., 2003, **20**, 855–863.
5. Rajeevan, M., Pai, D. S., Dikshit, S. K. and Kelkar, R. R., *Curr. Sci*., 2003, **86**, 422–430.
6. Gadgil Sulochana, Rajeevan, M. and Nanjundiah, R., *Curr. Sci*., 2005, **88**, 1389–1400.
7. Pattanaik, D. R. and Kumar, A., *Climate Dyn*., 2010, **34**, 557–572.
8. Preethi, B., Kripalani, R. H. and Krishna Kumar, K., *Climatic Dyn*., 2010, **35**, 1521–1539.
9. Rajeevan, M., Unnikrishnan, C. K. and Preethi, B., *Climate Dyn*., 2012, **38**, 2257–2274.
10. DelSole, T. and Shukla, J., *Geophys. Res. Lett*., 2012, **39**, doi:10.1029/2012GL051279.
11. Krishnamurti, T. N. and Kumar, V., *J. Climate*, 2012, **25**, 65–88.
12. Congwen, Z., Park, C.-K., Lee, W.-S. and Yun, W.-T., *Adv. Atmos. Sci*., 2008, **25**, 867–884.
13. Pattanaik, D. R. and Kumar, A., *Atmos. Sci. Lett*., 2014, doi:10.1002/asl2.513.
14. Suranjana, S. *et al*., *J. Climate*, 2013, doi:http://dx.doi.org/10.1175/JCLI-D-12-00823.1

ACKNOWLEDGEMENTS. I thank NCEP, USA for making available the real-time forecast for 2016 monsoon along with the hindcast data used in this study. I also thank the Director General of Meteorology; Head, Services and Head, NWP Division, India Meteorological Department, New Delhi for providing the necessary facilities to carry out this work. Thanks are also due to anonymous reviewers for valuable comments.

Received 21 October 2016; revised accepted 24 March 2017

D. R. PATTANAIK

India Meteorological Department,
New Delhi 110 003, India
e-mail: drpattanaik@gmail.com

Molecular characterization of *Cucumber mosaic virus* infecting wild betel (*Piper sarmentosum*)

Piper sarmentosum (Roxb.) belongs to the family Piperaceae, and is known by several names, including lolot pepper, la lot and wild betel. The local Indonesian name for this plant species is karuk. In Indonesia, karuk is used to treat asthma[1], abdominal pain, bone and teeth pain, and fungal infections[2]. In Malaysia, *P. sarmentosum* has been widely studied in terms of its antioxidant properties[3,4] and in Thailand, this plant has been investigated as a potential herbal medicine to treat diabetes[5].

Cucumber mosaic virus (CMV) has a wide host range and is capable of infecting more than 1000 species from 85 plant families[6]. The CMV genome consists of three positive-sense single-stranded RNA fragments along with two subgenomic RNA segments. The coat protein (CP) gene is encoded in the subgenomic RNA4 sequence[7,8]. CMV is classified into two major subgroups (I and II) based on serology, nucleotide homology and phylogenetic analysis[9,10].

During a viral disease survey of Piperaceae plant species conducted in Bogor, West Java, Indonesia in March 2005, mosaic symptoms typical of virus infections were observed on karuk leaves (Figure 1). A compound enzyme-linked immunosorbent assay with CMV antiserum (Agdia Inc., Elkhart, USA) was used for the early detection of viruses on symptomatic samples. The assay results indicated a positive reaction with high absorbance values (i.e. 2.8–3.0). Therefore, identification of CMV was confirmed through molecular characterization of the virus infecting karuk leaves. We studied

Figure 1. Mosaic symptoms on a karuk leaf.