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CALIBRATION OF PROBABILISTIC ENSEMBLE FORECASTS FOR INDIAN SUMMER MONSOON RAINFALL: A NON-GAUSSIAN APPROACH

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Abstract—**Due to the large variability of seasonal Indian summer monsoon rainfall (ISMR), the user community should be given probabilistic forecasts that convey the inherent uncertainty within the prediction. Probabilistic seasonal prediction can be done based on the general circulation models (GCM)'s outputs, however the output of these ensemble predictions cannot be used directly and requires further calibration in order to produce reliable forecasts. The common approach to make such probabilistic forecast is to calibrate the deterministic forecast from the model and then convert to probabilistic space using Gaussian distribution. Because neither observation for seasonal ISMR nor the GCM's forecast follow a Gaussian distribution, we introduce a non-gaussian model *viz.,* Extended Logistic Regression (ELR) for calibration method. ELR has been implemented on coupled GCMs of the North American Multi-Model Ensemble (NMME) project over 1982-2010 following a leave-one-year-out cross-validation manner. The skill of the proposed method has been evaluated against observed rainfall and found to be a good reliable and well calibrated forecast.**

I. MOTIVATION

A single deterministic rainfall forecast is not sufficient for predicting seasonal Indian summer monsoon rainfall (ISMR) which is characterized by large variability. The user community should be given probabilistic forecasts that convey the inherent uncertainty within the prediction. Though a plethora of study exists to make a deterministic model for predicting ISMR, only a few studies have described the probabilistic prediction system [1],[2]. These studies are mostly based on probabilistic multi model ensemble prediction based on the general circulation models (GCMs) in a Gaussian framework, i.e., calibrate the deterministic forecast from the model and then converting to probabilistic space using Gaussian predictive probability density function. Considering the fact that neither observation of seasonal ISMR nor the model's forecast followed Gaussian distribution, Logistic regression (LR) is an alternative approach [3]. LR is a nonlinear regression method where probability itself can be considered as the predictand rather than a measurable physical quantity. Separate prediction equations are derived to predict probabilities corresponding to different predictand thresholds in LR and yields a collection of threshold probabilities rather than full forecast probability distributions. However, the extension of LR by including the predictand threshold in the regression equations [4], namely Extended Logistic Regression (ELR), allows the derivation of full predictive distributions and avoid the problem of potentially incoherent forecast probabilities. In this study, ELR based calibration method introduced for the first time in seasonal prediction ISMR though it has been successfully applied in the past to ensemble weather forecasts. ELR has been implemented to the state-of-the-art coupled GCMs of the North American Multi-Model Ensemble (NMME) to make probabilistic prediction ISMR.

II. DATA AND METHOD

The lead-1 (using initial conditions of May) hindcast runs for the seasonal mean rainfall of June-July-August-September (JJAS) spanning over 1982-2010 from 9 global ocean-atmosphere coupled models that participated in the North American Multi-Model Ensemble (NMME) project [5] has been used in this

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study. These NMME monthly hindcast datasets are available to a common 1◦ resolution grid at http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME. The 1◦ gridded daily rainfall dataset from India Meteorological Department (IMD) is used as observational reference [6]. This daily data is further transformed into seasonal mean rainfall for JJAS for the same time period of the GCMs' hindcast (1982 to 2008).

ELR based calibration method is implemented in the following way to obtain the probabilities of the occurrence of tercile categories, *viz*., below, near, and above normal of seasonal mean ISMR

1) ELR has been fitted between each NMME model's predicted and observed rainfall dataset as below

$$\ln\left[\frac{p}{1-p}\right] = f(x) + g(q)$$

With $f(x) = b_0 + b_1\overline{x_{ens}}$ and $g(q) = b_2 q$

where p is the cumulative probability of not exceeding the quantile q, $b_s^{'}$ are regression coefficients and $\overline{x_{ens}}$ is the mean of all ensembles for individual model.

2) These resultant tercile probabilities from each of individual GCMs are then averaged together with equal weighting to obtain the final multi-model ensemble (MME) forecast.

3) The above-developed prediction scheme is done in a leave-one-out cross validation manner. Since the dataset contains only 29 years data (1982–2010), one year is retained and the model is developed for the rest of the 28 years and the predictand variable is estimated for the retained year. In this way, the cross-validated series for the predictand variable is generated and then validated against the observed rainfall data using skill scores mention in next section.

III. EVALUATION

The skill of ELR based MME prediction is evaluated against observation using reliability diagrams [7] to assess the reliability (degree of correspondence between issued forecast probabilities and relative observed frequencies), resolution (ability of the forecast system to assign probabilities different from the climatological probability), and sharpness (tendency of probability forecasts to approach 0 and 1) for each of the tercile categories. For Below and Above Normal categories, the reliability diagram is presented in Figure 1 by pooling all calibrated forecasts for 29 years and all grid points (357) over Indian land mass. Note that only bins with more than 1% of the total number of forecasts in each category are plotted in the diagrams. For both categories, the red lines (representing the forecast probability versus observed frequency) are close to the diagonal blue line (perfect forecast), indicating high reliability and well calibrated forecasts. The resolution has also improved as the angle of red lines with the horizontal (no resolution) is higher. However, the histograms superimposed on the reliability curves, showing how often forecasts of a given probability were issued over the hindcast period, are bell shaped indicating lack of forecast sharpness. In addition, ranked probability skill scores (RPSS)[8], a proper scores, used to quantify to which extent the probabilistic predictions are improved upon the climatological forecast of equal probabilities for each tercile category (i.e.1/3 for each of the tercile category). A positive (negative) value of RPSS indicates that the prediction system is better (worse) than the climatological guess, while zero refers no improvement over climatological forecast. The RPSS of the calibrated forecast is shown in Figure 2, in which the grid points having positive RPSS are shaded over Indian landmass, showed most of the country having positive RPSS. In conclusion, ELR based calibration methods provide high reliable forecasts with good resolution and better strategy compared to climatological probabilities. Though this paper concentrate only on the tercile probabilities events, with the advantage of making mutually consistent individual threshold probabilities, the proposed calibration method also developed a more flexible forecast format that allows users to glean information from those part of forecast distribution what matters most to them such as the probability of extremely dry/wet conditions.

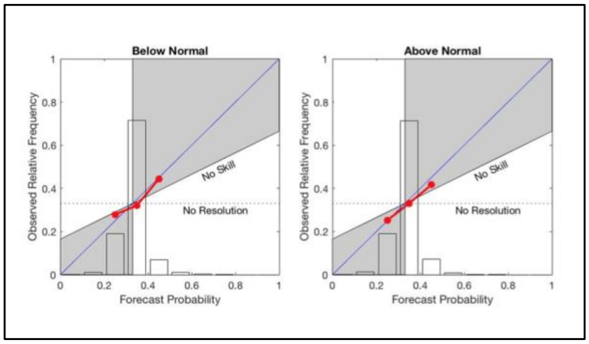

Figure 1. Reliability diagram for Below and Above Normal categories of ELR based calibrated MME forecast for seasonal ISMR during 1982 to 2010.

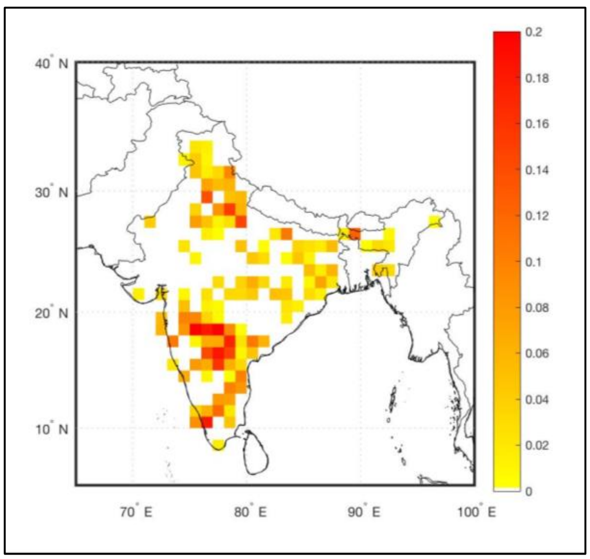

Figure 2. Ranked probability skill score of ELR based calibrated MME forecast for seasonal ISMR during 1982 to 2010.

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