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RESEARCH ARTICLE

Corroboration of Location Specific Seasonal Rainfall Forecast Using Australian Rainman for Tamil Nadu

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ABSTRACT

Skillful weather and seasonal predictions have significant socio-economic potential and could provide evocative information to farmers and decision-makers towards agricultural planning. The present study evaluates the Australian seasonal rainfall forecast model for the southwest and northeast monsoon of Tamil Nadu over the period from 2016 to 2020.. Different skill scores *viz*., Nash-Sutcliffe Efficiency (NSE), Ratio of Root Mean Square Error (RMSE) to the standard deviation of the observations (RSR), Per cent Bias (PBIAS), and Kling-Gupta Efficiency (KGE) were used for the present study to evaluate the performance of seasonal rainfall prediction by the Australian Rainman Software. The verification skill scores for both monsoons indicated that for southwest monsoon, especially the drought incidence (2016) was well captured by the Software. Inculcation of new climatic drivers, the performance of the northeast monsoon was also found to be within the acceptable range limit in recent years.

Keywords: *Seasonal Rainfall Prediction; Skill Score; Southwest; Northeast Monsoon*

INTRODUCTION

Weather and climate are significant drivers for all environmental and financial systems and central components that affect agricultural productivity and crop efficiency and effectiveness of agricultural systems. The seasonal rainfall over India is about 89 cm with 10% coefficient of variation (Rajeevan *etal.,* 2007). Tamil Nadu, positioned in southeast peninsular India, receives the major part of its annual rainfall during the northeast monsoon season.

The southwest monsoon, a part of the equatorial westerlies, is humid, unstable, and of considerable vertical extent. On the other hand, the northeast monsoon, which is a part of the northeast trades is reasonably dry, stable and of lesser vertical extent, about 1 to 2 Km (Selvaraj and Aditya, 2011).

The ENSO inflicts chaos on many tropical and subtropical regions of the world, disrupting normal patterns of rainfall to cause severe droughts and shattering flooding. The influences of climate variability are predominantly relevant in those countries pretentious by the El Niño/Southern Oscillation (ENSO) phenomena, such as Australia, Indonesia, southern Africa and India. The capability to understand, monitor, and predict this climatic variability offers an opportunity for the historical experiences to appraise alternative management approaches and make better quality decisions to gain during good years and minimize the losses during the poor years (Huda *et al.,* 1991; Pollock *et al.*, 2001).

Seasonal predictions of climate variables such as precipitation and temperature are frequently accessible as a probability of occurring within a confident category (Zhang and Casey, 1999). The apparent reason for providing a probability value is that probabilistic forecasts have the benefit that they can convey the uncertainty associated with the forecasts in a quantifiable way (Murphy 1977).

Verification of model forecasts is very imperative, because, it says how to make the best use of the forecasts at any weather prediction (Karuna Sagar, 2017). Verification of rainfall is crucial, as it is one of the important products with more practical application to the user community (Joseph *et al*., 2017). The present study explored the verification of location-specific seasonal rainfall predicted Australian Rainman software V(4.3) with the observed during both southwest and northeast monsoon by using different skill scores for Tamil Nadu

MATERIALS AND METHODS

Rainman Description

RAINMAN is a seasonal climate forecasting system developed by Queensland, Australia. It performs probabilistic prediction of rainfall at a seasonal lead-time based on discrete phases (i.e., positive, rapidly rising, negative, rapidly falling, and neutral; falling, rising, and neutral) of the Southern Oscillation Index (SOI) and/or SSTs.

RAINMAN aims to develop knowledge and skills for managing climate variability in agriculture by analyzing the effects of ENSO on rainfall to derive probability-based seasonal climate forecasts

The primary data was monthly historical observed rainfall for spatially different locations of Tamil Nadu and the length of the data was 40 years (1981-2020). Seasonal forecasts using the SOI were made in a similar way using the method of Clewett *et al.* (1991) and by utilizing the monthly values of the Troup SOI from the Bureau of Meteorology. The average value of the SOI in the three-month predictor period was used in the forecast period into three groups as follows: average SOI below – 5, –5 to +5, and above +5. Statistical significance was calculated using the nonparametric Kruskal-Wallis test (K-W) (Conover, 1971) and Linear Error in Probability Space (LEPS) skill scores (Potts *et al*., 1996).

Changes in seasonal forecast skill due to persistence were systematically examined for changes in the duration of the predictor period, lead-time, and forecast period. Lead-time (i.e. the time interval between the predictor period and the predictand period) was adjusted for three months for North East Monsoon (Oct-Dec) and four months for South West Monsoon (Jun-Sep). This was performed over a period of five years from 2016 to 2020.

Skill Scores

i. Nash-Sutcliffe Efficiency (NSE)

The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that governs the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970). This is a widely used and potentially reliable statistic for assessing the goodness of fit of hydrologic models.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{n}(Q_{obs} - \overline{Q_{obs}})^2}$$

Nash-Sutcliffe efficiencies range from $-\infty$ to 1. Essentially, the closer to 1, the more accurate the model is.

- ✓ NSE = 1, corresponds to a perfect match of model to the observed data.
- ✓ NSE = 0, indicates that the model predictions are as accurate as the mean of the observed data,
- ✓ $-\infty <$ NSE < 0, indicates that the observed mean is a better predictor than the model.

ii. Ratio of RMSE to the standard deviation of the observations (RSR)

Ratio of the RMSE between simulated and observed values to the standard deviation of the observations.

The RMSE observations standard deviation ratio (RSR) is calculated as the ratio of the RMSE and standard deviation of measured data. RSR varies from the optimal value of 0 to a large positive value. The lower RSR, the lower the RMSE and the better the model simulation performance.

The RMSE indicates a perfect match between observed and predicted values when it equals 0 (zero), with increasing RMSE values indicating an increasingly poor match. RMSE values less than half the standard deviation of the observed (measured) data might be considered low and indicative of a good model prediction.

$$RSR = \frac{\sqrt{\sum_{i=1}^{n}(|Q_{obs} - Q_{sim}|)^2}}{\sqrt{\sum_{i=1}^{n}(|Q_{obs} - \overline{Q_{obs}}|)^2}}$$

iii. Percent Bias (PBIAS)

Per cent bias (PBIAS) measures the average tendency of the simulated values to be larger or smaller than their observed ones.

$$PBAIS = 100 \times \frac{\sum_{i=1}^{n} Q_{obs} - Q_{sim}}{\sum_{i=1}^{n} Q_{obs}}$$

The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate overestimation bias, whereas negative values indicate model underestimation bias

iv. Kling-Gupta Efficiency (KGE)

The Kling-Gupta efficiency (*KGE*), which combines the three components of Nash-Sutcliffe efficiency (*NSE*) of model errors (*i.e*. correlation, bias, the ratio of variances or coefficients of variation) in a more balanced way, has been widely used for calibration and evaluation hydrological models in recent years. The KGE is a model evaluation criterion that can be decomposed in the contribution of mean, variance, and correlation to model performance.

In this implementation, the Kling-Gupta efficiency is defined as follows:

KGE = 1 - eTotal

eTotal is the euclidean distance of the actual effects of mean, variance, correlation and trend (optional) on the time series: eTotal = sqrt (eMean + eVar + eCor + eTrend) eTotal can be between 0 (perfect fit) and infinite (worst fit).Kling-Gupta efficiencies range from -∞ to 1. Essentially, the closer to 1 is the more accurate the model.

RESULTS AND DISCUSSION

Table 1. Verification skill scores for South West Monsoon (SWM) for Tamil Nadu (2016-2020)

SWM	NSE		RSR		PBIAS		KGE	
2016	0.70	A	0.50	A	14.2	UE	0.81	A
2017	0.25	A	0.85	A	-28.3	OE	0.67	A
2018	0.12	A	0.92	A	38.6	UE	0.50	A
2019	0.61	A	0.61	A	-19.6	OE	0.65	A
2020	0.39	A	0.48	A	13.0	UE	0.41	A

Note: A -Acceptable; UE- Under Estimate; OE- Over Estimate

Table 2. Verification skill scores for North East Monsoon (NEM) for Tamil Nadu (2016-2020)

NEM	NSE		RSR		PBIAS		KGE	
2016	-0.95	UN	1.37	UN	26.9	UE	0.01	UA
2017	0.54	A	0.67	A	-0.3	OE	0.50	A
2018	-0.14	UN	0.95	A	32.1	UE	0.50	A
2019	0.30	A	0.85	A	14.2	UE	0.50	A
2020	0.70	A	0.54	A	-5.6	OE	0.70	A

Note: A -Acceptable; UN- Unacceptable; UE- Under Estimate; OE- Over Estimate

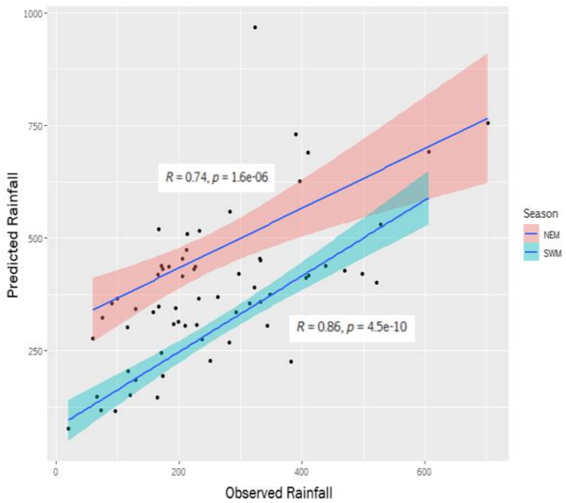

Figure 1. Predicted and observed rainfall of SWM and NEM in 2016

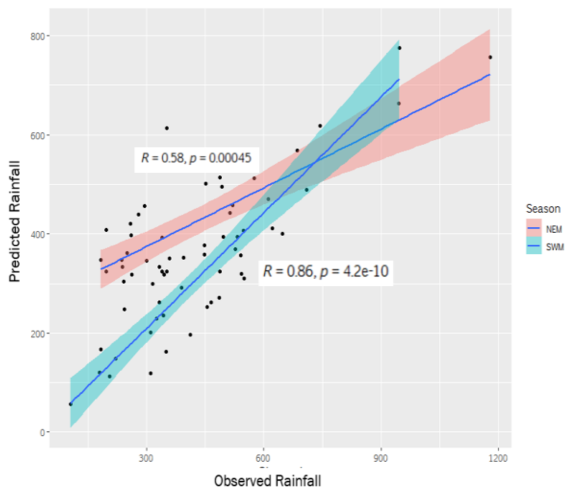

Figure 2. Predicted and observed rainfall of SWM and NEM in 2017

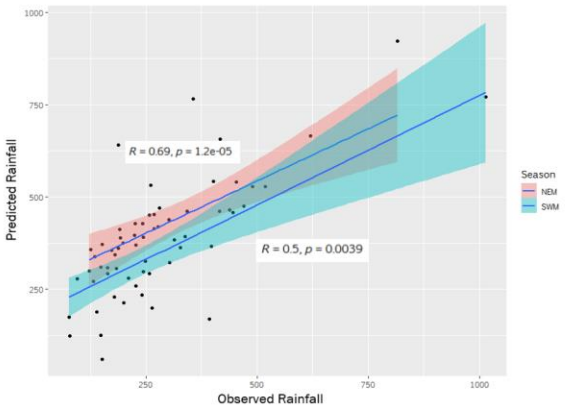

Figure 3. Predicted and observed rainfall of SWM and NEM in 2018

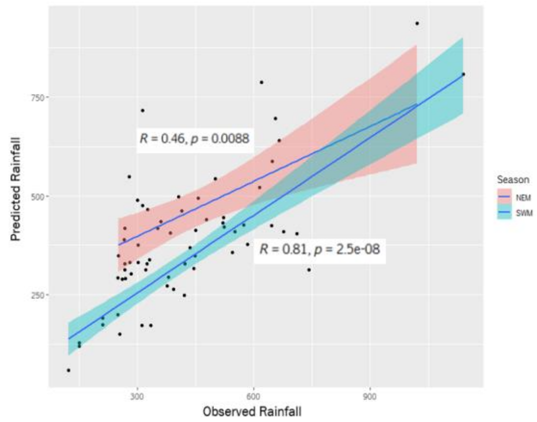

Figure 4. Predicted and observed rainfall of SWM and NEM in 2019

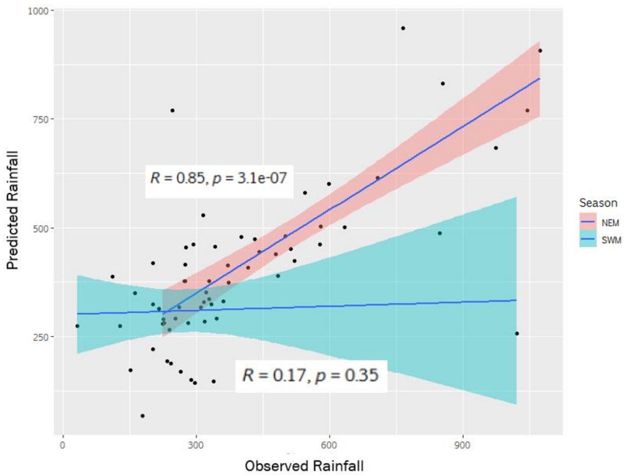

Figure 5. Predicted and observed rainfall of SWM and NEM in 2020

Prediction of seasonal rainfall for SWM and NEM (2016 to 2020)

Based on the scientific interventions, the location-specific seasonal rainfall forecast and observed rainfall values are given from 2016 to 2020 for both SWM (Figure 1a to Figure 1e) and NEM (Figure 2a to Figure 2e). Using the southern oscillation index values and sea surface temperature values prevailing over Pacific and Indian ocean for the month of April, the predicted values for SWM were given from 2016 to 2020. Similarly, the same mentioned phenomenon values for September were utilized for the forecasted values for the SWM from 2016 to 2020. The observed values were obtained from the India Meteorological Department and other research stations and colleges at the Tamil Nadu Agricultural University.

Verification of the model performance

The verification scores were performed for both the monsoon and are given in Table 3 and 4. Among the SWM over a period of five years, the NSE values ranged from 0.12 (2018) to 0.70 (2016) and the RSR values for all five years were found to be less than 1 which indicated the acceptable level of performance of the model prediction. It is quite interesting to note that, the model captures the historical drought event of 2016 in a better way where all the skill scores lied within the acceptable limit.

Except 2016 and 2018, the percent bias was underestimated in the rest of the years. Besides 2020, the KGE values were found to be from 0.50 to 0.81 which also supported the better performance of the model.

The verification for the 2016 NEM prediction revealed that the model performance was found to be unsatisfactory which was indicated by registering unacceptable values for all the skill scores. Over years, by trial-and-error methods, the inputs given in the model was tested verified with different global climate drivers and later, the performance of the NEM was found to be comes under the acceptable level of model performance.

CONCLUSION

Skill-scoring measurements have implications for the development of forecast models. Different skill scores viz., Nash-Sutcliffe Efficiency (NSE), Ratio of RMSE to the standard deviation of the observations (RSR), Percent Bias (PBIAS), and Kling-Gupta Efficiency (KGE) were used for the present study to evaluate the performance of seasonal rainfall prediction. The verification skill scores for both monsoons indicated that, SWM, especially the drought incidence (2016) was well captured by the Australian Rainman Software. Over years, due to inculcating climatic drivers, the performance of the NEM was also found to be within the acceptable range limit in recent years.

REFERENCES

Clewett, J.F., Howden, S.M., McKeon, G.M. and Rose, C.W. 1991. Optimizing farm dam

Conover, W.J. 1971. *Practical Non-Parametric Statistics*. *John Wiley and Sons*. pp. 256.

H. ZHANG AND T. CASEY, 2000. Verification of Categorical Probability Forecasts. *American Meteorological Society*, **15**:80-89.

Huda, A.K.S., Cogle, A.L. and Miller, C.P. 1991. Agroclimatic Analysis of Selected Locations in North Queensland, Bulletin QB91002. Queensland Department of Primary Industries, Brisbane, Queensland, Australia, 177 p.

Irrigation in response to climatic risk. In “Climatic Risk in Crop Production”. C.A.B. International. pp. 307-328.

M. Joseph, E. Murugan and M. Hemalatha. 2017. Forecast Verification Analysis of Rainfall for Southern Districts of Tamil Nadu, India. *Int.J.Curr.Microbiol.App.Sci.,***6(5)**: 299-306.

Murphy, A. H., 1977: The value of climatological categorical and probabilistic forecasts in the cost–loss ratio situation. *Mon. Wea. Rev*., **105**, 803–816.

Nash, J.E. and Sutcliffe, J.V. (1970) River Flow Forecasting through Conceptual Model. Part 1—A Discussion of Principles. *J Hydrology*, **10**, 282-290

Pollock, K.S., Meinke, H. and Stone, R.C. 2001. The influence of climate variability on cropping systems in Central Queensland. *Australian Agronomy Conference*, Hobart, Australia

Potts, J.M., Folland, C.K., Jolliffe, I.T. and Sexton, D. (1996). Revised “LEPS” scores for assessing climate model simulations and long-range forecasts. *J Climate* **9**: 34-53.

Rajeevan, M., Pai, D.S., Anil Kumar, R. 2007. New statistical models for long-range forecasting of southwest monsoon rainfall over India. *Clim Dyn* **28**, 813–828.

S. Karuna Sagar, G. Mrudula, K. Vijaya Kumari, S. Vijaya Bhaskara Rao. 2017.Verification of VARSHA Rainfall Forecasts for Summer Monsoon Seasons of 2009 and 2010. *Int J Cur Res Rev.***9(21)**:24-36.

Samuel Selvaraj, R and Raajalakshmi Aditya. 2011. Study on Correlation between Southwest and Northeast Monsoon Rainfall over Tamil Nadu. *Universal J Envirotl Res and Tech*.**1(4)**:578-581.