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The High Resolutions Improved Global Model Rainfall Forecasts of Seasonal Rainfall Using Statistical Downscaling Methods Over South Asia

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ABSTRACT

This study deals with two statistical downscaling (SD) techniques for their potential to improve the skill of forecasts seasonal rainfall over core monsoonal belt regions over South Asia. It constitute most comprehensive to date inter-comparison of SD methods. This work uses Indian Summer Monsoon (ISMR) forecasts from global primary models during 1996 to 2010. Two popular downscaling methods were tested by using unequal weight to all studied models which is termed as Best Linear Unbiased Estimator (BLUE) or by equal weight known as Ensemble Mean (EM). The statistical downscaling methods Bias Correction and Spatial Downscaling (BCSD) and Bias Correction and Constructed Analogue (BCCA) from Model Output statistics (MOS) approach were used. The analysis of direct models forecasts reveals that the bias is high with respect to season across South Asia, hence the necessity of SD. Though the skill of SD methods varies strongly depending on regions and seasons considered, both BCCA and BCSD also reveal higher performance than any primary models. The BCCA SD models are most capable to forecasts ISMR even at local scale than any others.

1. Introduction

[i]The impact of seasonal weather variability has always an importance for water management transportation, etc. in all over world, especially in Asia. Naturally, monsoon (ISMR) plays anexigent role for agricultural production. The multi-decadal climate dynamics and climate change projections are generated using the primary Global Climate Models (GCMs) (Taylor, Stouffer, and Meehl, 2011). However, the forecasts from the primary modelsat coarse resolutions suffer from biases (Flato *et al*., 2013). Therefore, most analyses of these model skills are useful for the study of the broad spatial and temporal resolutions, but it is limited in case of analyzing the seasonal rainfall forecasts at local spatial scales

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(Chakrabarty and Krishnamurti(2006)). However, there is opportunity to apply different model averaging techniques with equal and unequal weighting of individual models for generating more improved forecasts. The multimodel methods were introduced to bridge this gap by researchers (Zhang and Krishnamurti 1997; Molteni *et al*. 1996; Toth and Kalnay 1997). Du (2007) and Qi *et al*. (2014) have shown that the simple equal weighted ensemble method improves the forecasts' skills. Moreover,the weighted ensemble methods are more acceptable to improve forecasts skills. Krishnamurti *et al.* (1999) has shown improvement to forecast seasonal weather. Various institutions like National Center for Atmospheric Research (NCEP) (Toth and Kalnay, 1993) and Canadian Meteorological Center (CMC) have developed rainfall forecasts using multimodel methods for its usefulness. Krishnamurti *et al.* (1999, 2000a, b, 2009) have again used the principle of multiple linear regression to improve the multimodels, namely, superensemble. Ensemble forecasts are more advantageous for probabilistic forecasts also (Zhu *et al.* 2013).

1.1 Downscaling: Also two downscaling methods have been developed in early of Maraun *et al*., (2010): Dynamical Downscaling (DD) & Statistical Downscaling (SD). Many downscaling studies have been carried out till now for the forecasts of seasonal rainfall (Leung *et al.*, (2003)). The various impacts of global warming play a vital role in weather change on small scale. So it becomes necessary to develop and apply the methodology to specific issues of a region (Cohen (1990)).

1.2 Statistical Downscaling (SD): SD methods confide on statistical models. Statistical downscaling method establishes statistical relationship between local scales (finer resolution information) predictand of interest and GCMs outputs (predictors) (Fowler *et al*. (2007).

This article presents two fold cross-validation experiments with MOS methods. This work establishes the most comprehensive to date comparison of downscaling methods from MOS approach on local scale over south Asia.

2. The Study Area and Experimental Data

South Asian monsoon and East Asian monsoon together constitute Asian monsoon. China Japan and Korea are affected by East Asian monsoon. South Asian monsoon is affected by Indian monsoon. Indian monsoon can be classified into four core monsoonal regions. In this work Statistical Downscaling has been conducted over North East Indian (NEI) region.

2.1 GCM Predictors: GCM predictors data set was used considering daily surface rainfall from six primary models.

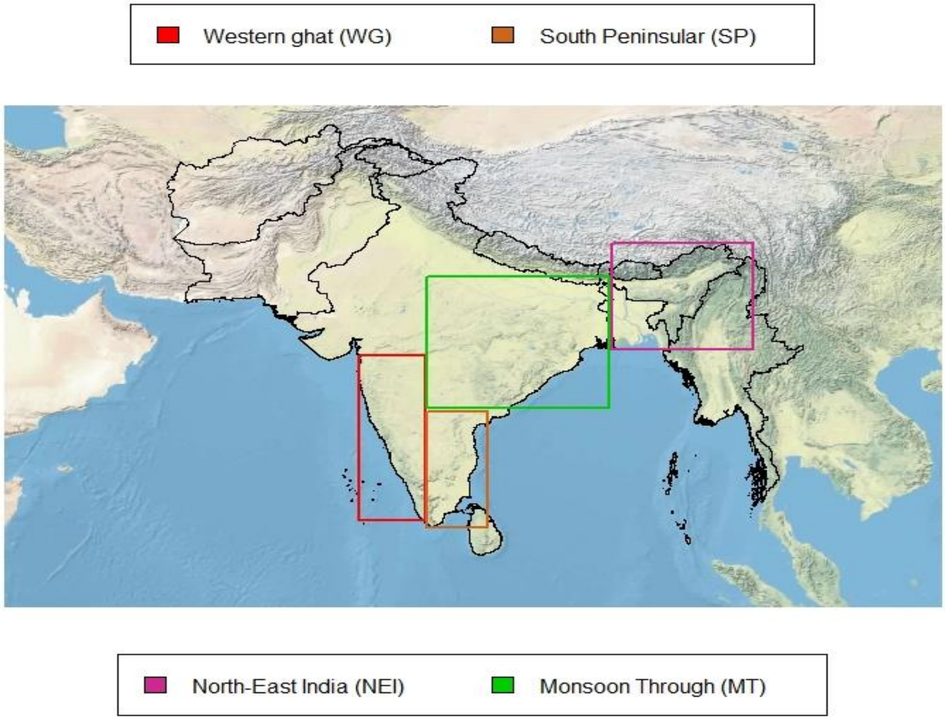

Figure 1: The coloured boxes show the four core monsoonal belt regions over South Asia. The names of the different regions have been indicated as a legend at the top and bottom of the figure.

2.2 Dataset Used in this Study: The latest version of North American Multimodel Ensemble **(**NMME) forecasts system was considered in this work.

Table 1: detail descriptions of all global models participated in this study.

Institute Name and Reference	Models	Analysis Period	Ensemble Size	Lead Time (Month)	Model Explanation	Model Resolution (Atmosphere)	Model Resolution (Ocean)
NCEP Saha *et al.* (2014)	CFSv2	1996-2010	24	00-09	Climate Forecast System Version 2	T126L64	MOM4L40 0.250 EQ
CMC Merryfield *et al.* (2013)	CMC1 and CMC2	1996-2010	10	00-11	Canadian Meteorological Centre	CanAM3T63L31	CanOM4L40 0.940EQ
GFDL Delworth *et al.* (2006)	GFDL CM 2.1	1996-2010	10	00-11	Geophysical Fluid Dynamics Laboratory Climate Models Version 2	2x2.50L24	MOM4L50 0.30EQ

NASA Vernieres *et al.* (2012)	GEOSS2S	1996-2010	10	00-11	National Aeronautics and Space Administration	1x1.250L72	MOM4L40 0.250EQ
NCAR Kirtman and Min (2009)	CESM1	1996-2010	10	00-11	National Center for Atmospheric Research	T85L26	POPL42 0.30EQ

3. Methodology for Developing Weather Models' Forecasts

The conventional models used in the multimodel ensemble are BLUE and EM.

3.1 BLUEUnequal weighted Method: It is difficult to derive the weights for each spatial grid points for all models. Xie and Akrin (1996) and Ali and Ghosh (2022) have illustrated an error adjustment technique for minimization of models errors. It may be adopted to construct new estimators which provide seasonal forecasts with better skills for the Indian region. For each grid points an error E_i (say) may be calculated from selected models. Then the calculated errors of each models may be denoted as.

$$E_i(x,y,z,t) = O(x,y,z,t) - T_i(x,y,z,t) \text{ for } \quad i = 1\ (1)n \tag{1}$$

$O(x,y,z,t)$ = Observations and $T_i(x,y,z,t)$ = ith model forecast at time t. Now the estimate of error σ_i^2 is denoted as

$$\sigma_i^2(x,y,z) = \frac{1}{n}\sum_{i=1}^{n} E_i^2(x,y,z,t) \tag{2}$$

The weights w_i is denoted by

$$w_i(x,y,z) = \frac{1}{\sigma_i^2}$$

The estimator $\hat{X}$ is defined as follows.Then, the calculated residual V_i at time for next step is written as

$$V_i(x,y,z) = \hat{X}(x,y,z) - T_i(x,y,z)$$

$$V = \alpha\hat{X} - T$$

$$V = [V_1, V_2, V_3, \ldots\ldots, V_N]^T, \alpha = [1,1,1,\ldots\ldots,1]^T, T = [T_1, T_2, T_3, \ldots\ldots, T_N]^T$$

$$W = \begin{bmatrix} w_1 & 0 & \dots & 0 \\ 0 & w_2 & \dots & 0 \\ : & : & \dots & : \\ 0 & 0 & \dots & w_N \end{bmatrix}$$

$$\hat{X} = (\alpha^T W \alpha)^{-1} \alpha^T W T$$

$$\hat{X} = \frac{\sum_{i=1}^{N} w_i(x,y,z) * T_i(x,y,z)}{\sum_{i=1}^{N} w_i(x,y,z)}$$

3.2 Ensemble Mean (EM):

$$\hat{X} = \frac{\sum_{i=1}^{N} T_i(x,y,z)}{N} = EM$$

3.3 BCCA Method

Bias Correction and Constructed Analogues (BCCA) method is a statistical downscaling method that is used to forecast ISMR. It was introduced by Hidalgo ~~e~~*t al*. (2008) and Maurer *et al.* (2010).

3.4 BCSD Method: Bias Correction and Spatial Downscaling (BCSD) is aStatistical downscaling method that is also used to forecast ISMR. General Circulation Models (GCMs) can produce weather forecasts at 1^0 x 1^0 resolutions. Salathe (2007) has shown that the BCSD method can produces promising downscaling results for the prediction of weather variables from GCM outputs and the assessment was made for effects of those hydrological factors on weather change (Maure and Hidalgo (2008)).

4. Results

4.1 Rainfall forecast skills over North-East India

The skill matrices have been computed and analyzed primarily to evaluate the performance of forecasting models.

Table 2: The skill matrices to forecast ISMRin training period as well astest period, statistically significant (at 95% level) if r greater than 0.5.

Matrices		SD Methods	CFSv2	CMC1	CMC2	GFDL	NASA	NCAR	EM	BLUE
r	Training	Direct	-0.03	0.40	0.19	0.11	-0.07	-0.29	0.10	0.10
	Test	BCCA	0.93	0.92	0.93	0.93	0.92	0.91	0.92	0.94
	Test	BCSD	0.87	0.87	0.87	0.91	0.85	0.87	0.87	0.89
NSE	Training	Direct	-0.49	-0.20	-0.31	-0.78	-0.75	-1.10	-0.55	-0.50
	Test	BCCA	0.63	0.63	0.66	0.57	0.64	0.65	0.62	0.72
	Test	BCSD	0.58	0.34	0.58	0.43	0.26	0.58	0.65	0.42
RMSE	Training	Direct	6.61	5.94	6.21	7.21	7.14	7.83	6.74	6.62
	Test	BCCA	1.93	2.37	1.94	2.16	2.09	1.95	2.05	1.72
	Test	BCSD	2.47	3.18	2.54	2.72	3.21	2.47	2.38	2.78
MAE	Training	Direct	4.87	4.08	4.28	5.24	5.05	5.68	4.73	4.75
	Test	BCCA	1.57	1.92	1.56	1.70	1.64	1.54	1.65	1.33
	Test	BCSD	1.88	2.33	1.92	2.06	2.51	1.88	1.79	2.08

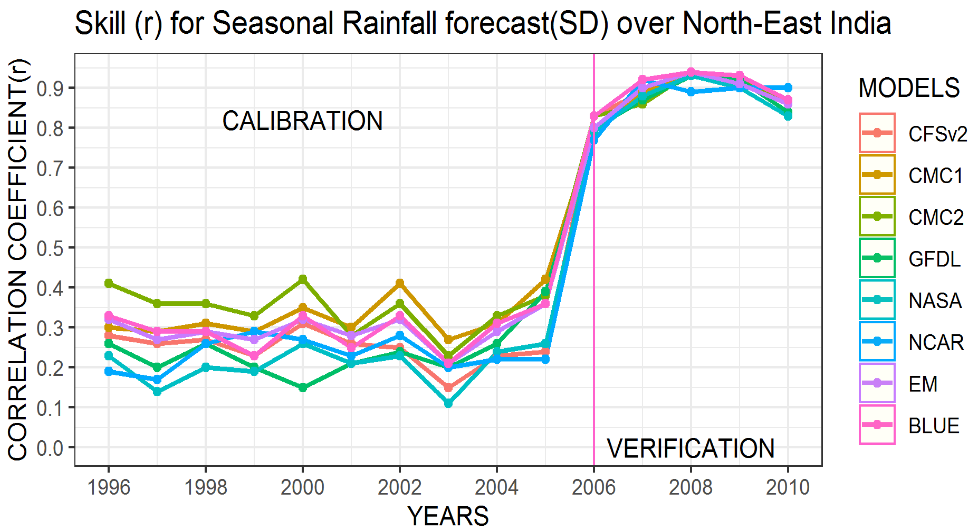

Figure 2: The Correlation Coefficients (r) between observed and predicted from primary global models, EM and BLUE.

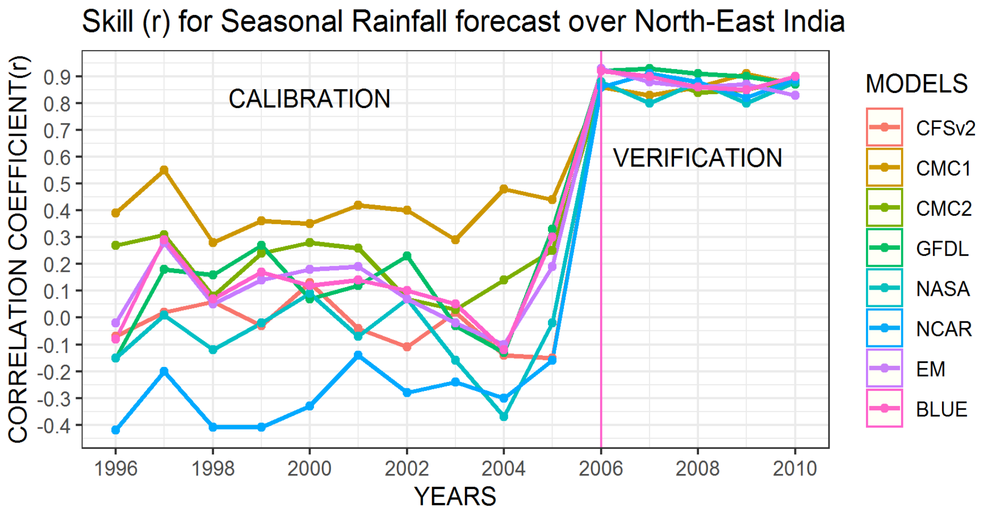

Figure 3: Nash Sutcliffe Efficiency (r) between observed and predicted from primary global models, EM and BLUE.

The correlation coefficient (r) and root mean square error (RMSE) are two metrics to assess the performance of the model forecasts and of the results by comparing with the observations (Wilks (2011)). The RMSE reflects the total bias of the simulations and the results compared to the observations. The Mean Absolute Error (MAE) reflects the average errors between the forecasts from models and the observations.

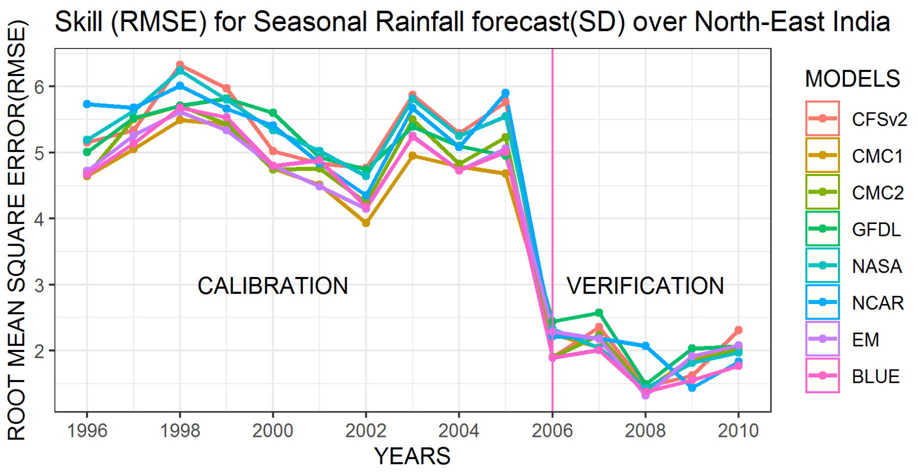

Figure 4: The Root Mean Square Error (RMSE) between observed and predicted from primary global models, EM and BLUE using BCCA.

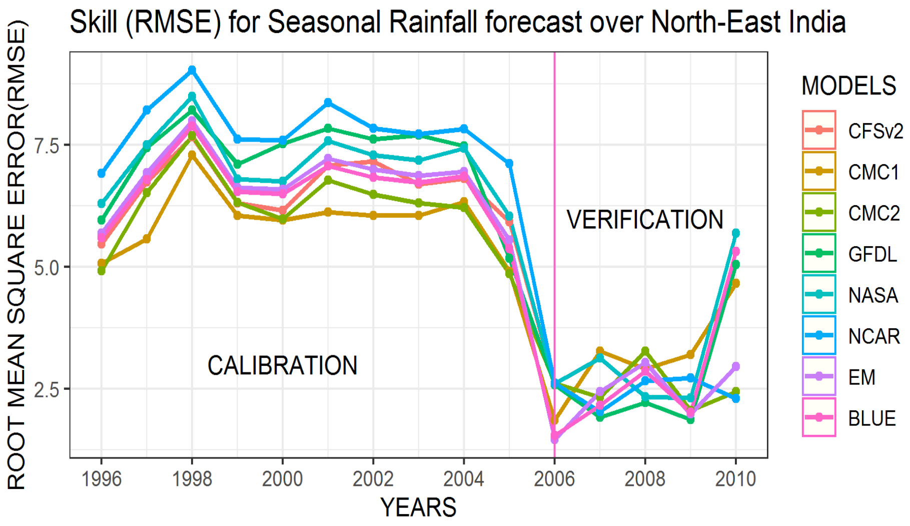

Figure 5: The Root Mean Square Error (RMSE) between observed and predicted from primary global models, EM and BLUE using BCSD.

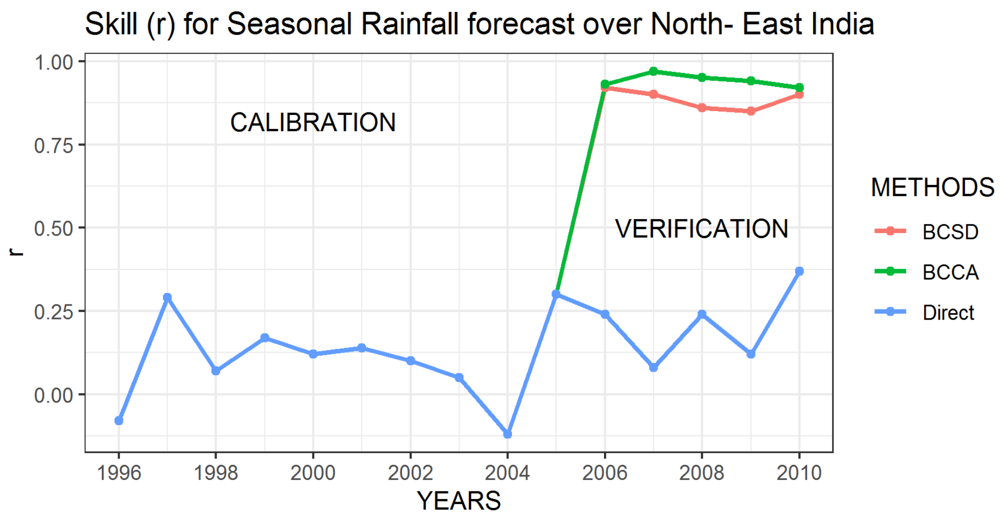

Figure 6: The spatial Correlation Coefficients (r) between observed and predicted from BLUE.

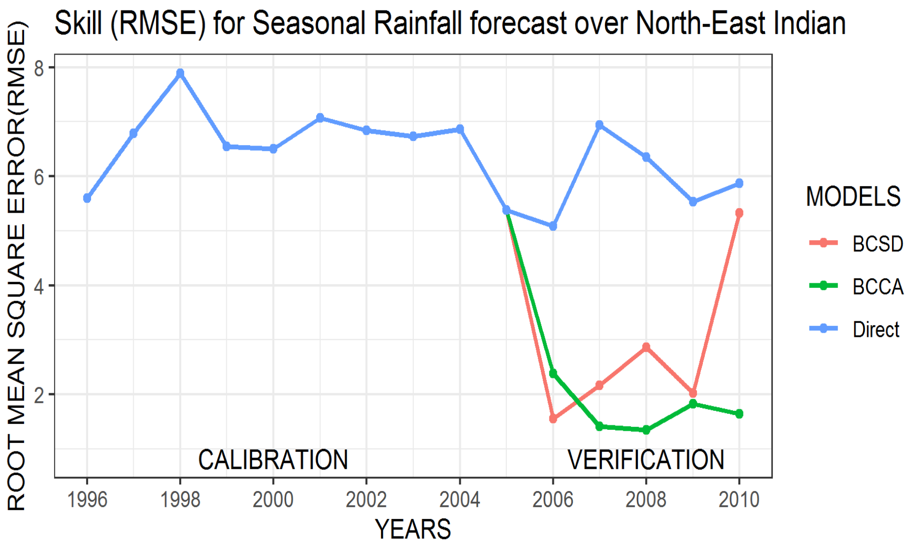

Figure 7: The Root Mean Square Error (RMSE) between observed and predicted from BLUE.

The primary models forecasts with correlations of -0.03, 0.40, 0.19, 0.11, -0.07, -0.29, 0.10 and 0.10. But after downscaling the correlations are 0.87, 0.87, 0.87, 0.91, 0.85, 0.87, 0.87, 0.89 (BCSD) and 0.93, 0.92, 0.93, 0.93, 0.92, 0.91, 0.92 and 0.94 (BCCA). The model provides forecast with wet bias in excess of 12 mm/day for some parts of Assam, few parts of Nagaland, Manipur, Mizoram, Tripura and Meghalaya with BCCA SD models.

4.2 The Overall Forecasting Skills: The average skills were calculated over seasons and selected space. Table 2 presents the overall skill scores over selected region for BCCA and BCSD downscaling methods and each primary and conventional model for one month lead time. The skills are weak for forecasting seasonal rainfall over each selected regions from primary and conventional model both whereas BCCA and BCSD downscaling methods showed relatively higher skills for each models.

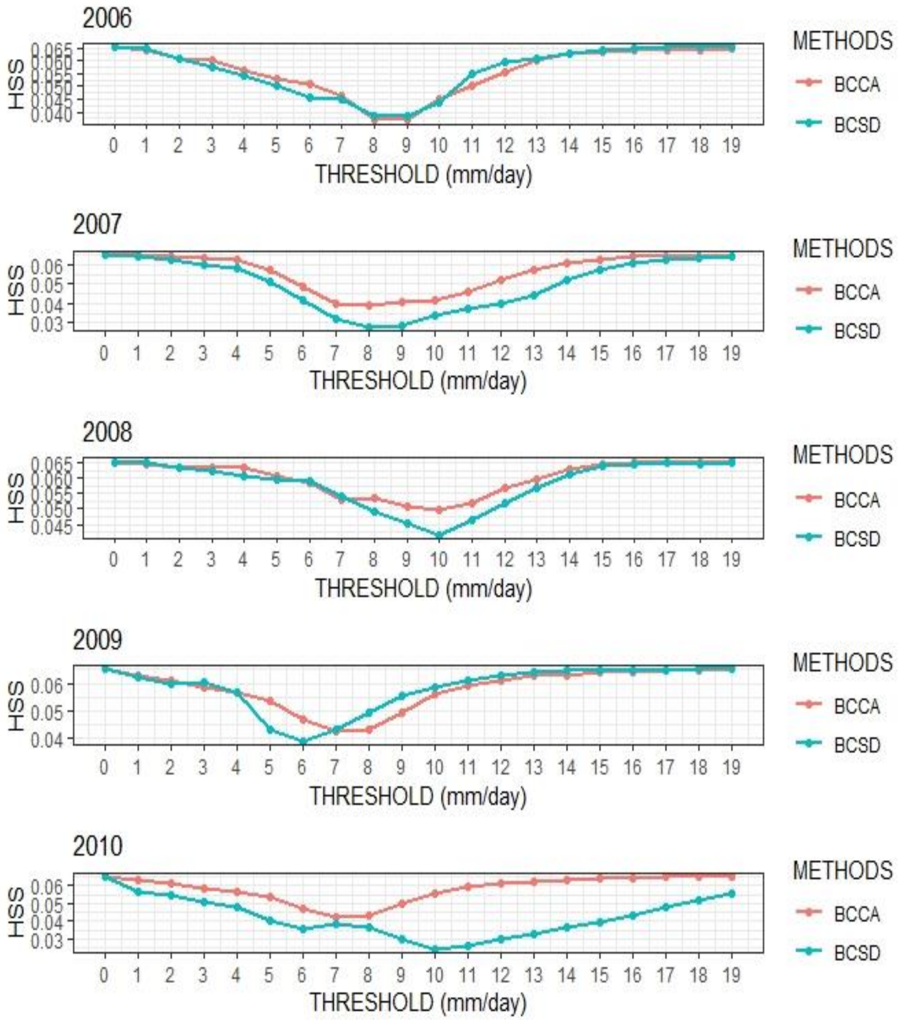

Figure 8: Heidke Skill Score (HSS) for conventional models for the prediction of JJAS seasonal rainfall over Indian region.

4.4 Heidke Skill Score (HSS): In this work Heidke Skill Score (HSS), a well-known metric, is used to measure forecast accuracy as described by Cohen's. It ranges from minus infinity to 1. It is perfect skill with value 1and 0 means no skill. Also here HSS has been considered to measure or inter-comparison the skills of different forecasting models. Hogan *et al.* (2010) preferred HSS than Equitable Threat Score (ETS) to measure the skills of multimodel. From the HSS values, it can be noted that BCCA performs uniformly better than BCSD method as shown in Fig. 8. BCCA predicts the rainfall with similar accuracy as of BCSD for the threshold value greater than 15 mm/day only. Therefore, it may be noted that the downscaling method BCCA can provide significant improvements for the forecast of rainfall over North-East India (NEI).

5. Conclusions and Further Work Possibilities

The conventional BCCA SD models BLUE and EMare best to predict seasonal rainfall over studied region than any others. The skills from the BCCA BLUE method are always higher than any others. So the BCCA downscaling methods may be adopted which improves the forecasts at desired resolutions.

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