1. Introduction:

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The General Circulation Models (GCMs), one of the most important tools for monthly and seasonal scale forecast, have errors in predicting meteorological parameters; particularly the error is large in predicting rainfall over India (Kang et al. 2004; Kang and Shukla, 2005; Krishna Kumar et al. 2005; Wang et al., 2005; Barnston et al. 2010). The evaluation of GCMs using long-period simulations in hindcast mode clearly unveils that although GCMs could predict large-scale upper air features satisfactory but rainfall prediction is poor (Wood et al., 2004). Therefore, it is necessary to use appropriate statistical bias correction techniques to correct the rainfall forecasts from the GCMs products. Statistical bias correction methodologies act on model outputs to remove the systematic bias. Consequently, the statistical properties of the corrected data match those of those observations. A limited number of studies are available on the bias correction of GCMs (Kharin and Zwiers, 2002; Hashino et al., 2006; Ines and Hansen, 2006; Sajani et al., 2007; Li et al., 2010; Feudale and Tompkins 2011). These studies proposed different transfer functions, which remove bias from the GCM raw outputs. Kharin and Zwiers (2002) described the simple and regression based bias corrections on 500 hPa geopotential height forecasts derived from the Atmospheric Model Intercomparison Project (AMIP). Hashino *et al* . (2006) evaluated three bias correction methods for ensemble stream flow volume forecasts for the Des Moines River basin. The results showed that all three bias-correction methods significantly improved the forecast quality by eliminating unconditional biases and enhancing the forecast skill. Ines and Hansen (2006) showed the improvement of daily rainfall forecast by ECHAM4p5 GCM (developed at the Max–Plank Institute, Germany) after using a quantile based bias correction. Li *et al* . (2010) also used the same technique for the Intergovernmental Panel on Climate Change AR4. Sajani *et al* . (2007) showed the skill of multiple linear regression based bias correction implemented on the 12 ensemble member of the Meteorological Research Institute (MRI) model by Japan Meteorological Agency for simulating ISMR. Feudale and Tompkins (2011) applied empirical orthogonal function based bias correction techniques on the operational seasonal forecasts made by the European Centre for Medium Range Weather Forecasts (ECMWF) for the West African monsoon region. The correction technique was found to improve the location of monthly and seasonal average precipitation anomalies. Piani *et al* . (2009) showed that an improvement in forecast can be made by using statistical bias correction of the Danish Meteorological Institute (DMI) regional model over Europe. Haerter *et al* . (2011) proposed a cascade bias correction method on precipitation and temperature forecast by ECHAM5 GCM, forced by the IPCC B1 emission scenario 5 for future climate. Fan *et al* . (2011) used a simple bias correction method to correct the daily operational ensemble week-1 and week-2 precipitation and 2m surface air temperature forecasts from the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS). Although it has been found that a large portion of these forecast errors are removable, the effectiveness is time and space dependent. Nevertheless, these studies revealed the significant effect of bias correction on GCM products. However, these improvements are restricted to the specific time scale of the fluctuations that are considered. For example, same statistical bias correction for daily values may not work on a monthly scale (Haerter *et al* ., 2011).

Although the literature discussed above is in the context of bias correction of GCMs over the globe, only a few studies are available in the context of the Indian Summer Monsoon rainfall (ISMR), where attempts have been made to evaluate the skill of different bias correction techniques. The main objective of the present study is to evaluate different statistical bias correction methods of a GCM output. The novelty of the present study lies in the fact that it attempts:

* To find a robust bias correction method for ISMR.

* To examine whether the existing skill metrics such as climatology, root mean square error is appropriate to evaluate the bias corrected rainfall.
* To examine that how far the bias corrected rainfall is able to capture the extreme cases.

2. Bias Correction Techniques:

There are many techniques for bias corrections, which are divided in two groups. First is transformation technique and second one is without transformation technique. While without transformation method shows a statistical function is constructed to remove the biases and in transformation case, the biases are estimated explicitly and the model product is corrected by adjusting the biases. Suppose $F_{i,t}$ (i varies from1to n ; n= number of members) is the rainfall predicted by i^{th} member of a model and Y_t is observed rainfall at time t where the mean of ensemble members refer as .

2.1. Without Transformation Functions (WOTF):

In this process, bias is removed from the model's forecast without any transformation function. In WOTF, the following methods are used.

2.1.1. Mean Bias-remove Technique (U):

In this technique, the mean bias is adjusted in every year. Mean bias is defined as the difference between observed climatology () and climatology of ensemble mean ():

Eq. (1)

For each year this difference (b_t) is calculated in the leave-one-out cross validation manner and adds this mean bias in the 'test' (t) year's model mean i.e.

Eq. (2)

Where, is the bias corrected forecast for the t^{th} year; is the calculated bias. For example, if a user has observed and model data for the period 1982-2008 and the bias correction for the year 2008 is calculated, then is calculated on the basis of the data from 1982 to 2007. This indicates that the model and observed climatology will be calculated for the 1982-2007 period (leaving the predicted year) to calculate. Now, bias corrected rainfall () of the year 2008, the ensemble mean of that model () for 2008 is added to the calculated (as defined in Eq. (2)). Kharin and Zwiers (2002) described this method as bias-removed individual forecast.

2.1.2. Multiplicative Shift Technique (M):

Ines and Hansen (2006) applied this simple method. In this method the ratio between observed climatology () and the climatology of the ensemble mean (), that is, Eq. (3)

The is calculated first in the leave-one-out cross validated manner. For example, if a user has observed and model data for the period 1982-2008 and the bias correction for the year 2008 is calculated, then is calculated on the basis of the data from 1982 to 2007. This implies that the model and observed climatology will be calculated for the 1982-2007 period (leaving the predicted year) to calculate.

Then it is multiplied with the model mean for obtaining the bias corrected rainfall by the following equation,

Eq. (4)

The process where, is the bias corrected forecast for the t^{th} year; is the calculated bias in cross validation mode, and the ensemble mean of that model for the t^{th} year. For example, for observed and model datasets for the period 1982-2008, and m_{2008} will be calculated by taking the ratio between observed and model climatology for the period 1982-2007. Bias corrected forecast for the year 2008 will then calculated by multiplying the with ensemble mean model forecast for the year 2008.

2.1.3. Standardized Technique (Z):

Standardization is the easiest bias-correction method to rectify the systematic error in the mean rain fall amount .It is also a simple bias correction technique introduced by Pan and van den Dool (1998). In their study, the standardization process is implemented for both model and observation before making the probabilistic forecast. This technique adjusts the systematic error for the model. After standardization, the magnitude of the ensemble mean and observation lies in a certain range, so that the bias is almost zero. However, it is not recommended to disseminate anomaly when giving a deterministic forecast to the end user. Therefore, after the standardization of the ensemble mean, the observed climatology and standard deviation were reconstructed. In other words, it was assumed that the standardized anomaly of the ensemble mean is:

Eq. (5)

Where, is the ensemble mean of the t^{th} year, is the climatology of model ensemble mean, and is the standard deviation of model ensemble mean; the climatology and standard deviation are computed in the leave-one-out cross validation mode by leaving the forecasted year (here t^{th} year). The leave-one-out cross validation method is same as discussed above. In generating the forecast in a deterministic value (Z_t) , the forecast is reconstructed with the observed climatology () and observed standard deviation by the equation below:

Eq. (6)

Where, is the bias corrected forecast for the t^{th} year.

Therefore, in this method the long-term climatology and standard deviation of the observation is directly projected in the ensemble mean by the cross validation procedure.

2.2. With transformation functions (WTF):

In this process, bias is corrected by statistical transformation function such as fitting or mapping between observation and model output. The following WTFs are considered in generating bias corrected forecast.

2.2.1. Regression Technique (R):

In this method, a regression model is constructed between observation (Y) and the ensemble mean of the model ( )by the following equation:

Eq. (7)

Where the coefficient of the regression equation is estimated by the least square estimates i.e.

Eq. (8)

and

Eq. (9)

is the bias corrected forecast for the t^{th} year.. The regression coefficient (slope) and regression constant (intercept) are calculated by the leave-one-out cross validate manner. This regression coefficient rescales the forecast to correct the systematic errors (Kharin and Zwiers, 2002).

2.2.2. Quantile Mapping Method (Q):

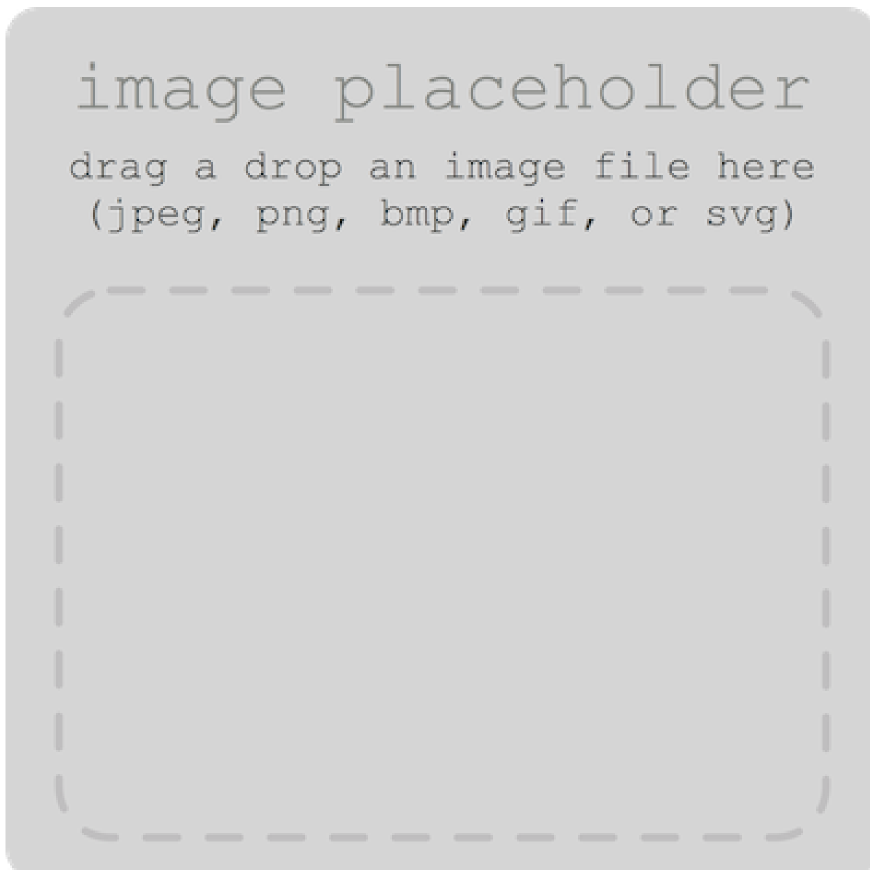
A ' quantile-based' bias correction approach is useful to statistically transform rainfall simulated by a GCM to bias corrected data and to make it applicable for the use in impact assessment model. This method is also referred to as 'histogram equalization' and/or 'rank matching' (Wood et al., 2002; Hamlet et al., 2002;

Piani et al., 2009). The statistical bias correction method employed in this study is based on the initial assumption that both observed and simulated intensity distributions are well approximated by the gamma distribution.

In the quantile mapping method, empirical probability distributions of observed and forecasted values are used. The bias corrected output is the inverse of the cumulative distribution function (CDF) of observed values at the probability corresponding to the model output CDF at the particular value. In the quantile mapping method, the bias is not calculated explicitly. Suppose CDFs, for observed data and for ensemble mean of model forecast are known. For the bias corrected value Q will then be as follows:

Eq. (10)

Here, is an inverse of CDF. Thus, the quantile mapping procedure is a transformation between two CDFs. The whole procedure is implemented in the leave-one-out cross validation way. [Y-Axis should be CDF]



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2.2.3. Principal Component Regression (PCR):

The principal component analysis (PCA) is found appropriate when a large number of observed variables exists which may contain some redundancy and necessary to develop a smaller number of artificial variables (called principal components) which are uncorrelated. Thus, PCA reduces a dataset containing a large number of variables to a dataset containing a fewer new variables. These new variables are linear combinations of the original ones, and these linear combinations are chosen to represent the maximum possible fraction of the variability contained in the original data. Sajani *et al* . (2007) implemented multiple linear regressions on the member to find a bias corrected weighted ensemble mean. They used 23 years to make the multiple linear regression models. Although the number of predictors is less than to the total number of years, it is not sufficiently less. So, there is a high chance of over fitting and the presence of multicolinearity among the members may affect the estimated coefficient adversely (Fisher, 1922). Therefore, instead of using all the members, one should screen them on the basis of principal component analysis. By use of principal component analysis, one can choose the predictors, which contribute the maximum to the explained variance. Principal component analysis (PCA) based regression is introduced for improvement over the work of Sajani *et al* . (2007). In this method, at first the PCA is done on members and only such modes which explain a high amount of variance are retained for further simple multiple linear regression. It is general practice to consider that many of principal components (PCs) which can explain more than or equal to 80% of the variance. In the present study, minimum number of PCs is chosen to explain 90% of the variance for the regression. The PCs being orthogonal and the multicolinearity is removed. This whole procedure is carried out in same type of leave-one-out cross validation mode as discussed earlier.

3. Performance Evaluation of Bias correction Techniques:

After implementing of these techniques, it is necessary to estimate the skill/quality of these techniques i.e. which method is reproducing data closer to the observations. In this section, all the bias correction techniques stated above are applied to the summer monsoon rainfall averaged over all-India. Model raw outputs (no bias correction; NBC) and the bias corrected outcomes are evaluated with the observations. The quality of bias-corrected rainfall on monthly scale is evaluated using the different skill-score test viz. Climatological mean**,** standard deviation, root mean square error, index of agreement, correlation coefficient.

The majority of studies of bias correction methods have examined the bias corrected rainfall in the view of climatology and/or root mean square error (RMSE). In the present study, some others skill scores along with climatology and RMSE have been used to examine all the methods in a more meticulous way.

3.1. Climatological mean:

The observe climatology for the study period (1982–2008) is 7.63 mm day^{-1} whereas the climatology of NBC is 5.68 mm day^{-1}, which is much lesser than the observation. All of the bias correction methods are able to capture the long term mean or climatology. Actually, all of the methods are capable of adjusting the long-term mean biases. Therefore, there is a significant improvement in the removal of the bias in climatology by each method.

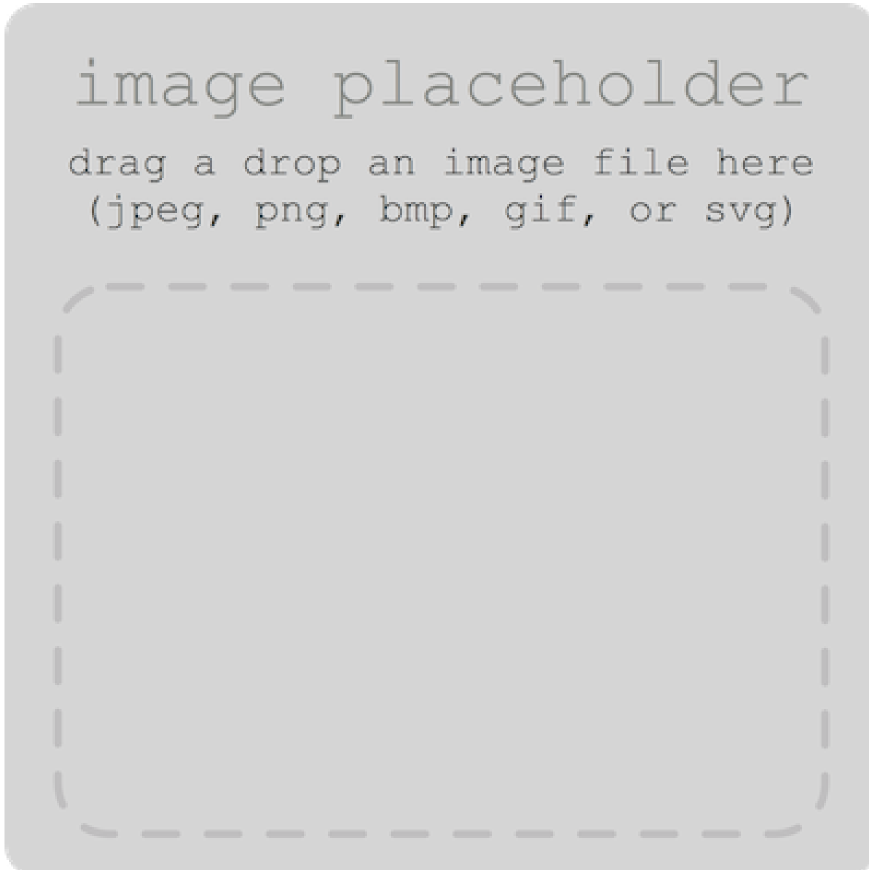
Table 1: Skill scores of CFSv2 for JJAS all India rainfall for the period 1982-2018 without bias corrected model (NBC) and all bias correction techniques: mean bias-remove technique (U), multiplicative shift technique (M), standardized-reconstruction technique (Z), regression technique (R), quantile mapping method (Q) and principal component regression (PCR) along with observation.

Figure 1: Interannual variability of rainfall from observation, raw model and six bias correction methods for June–July–August–September (1982–2008).

The above table shows Skill scores for not bias corrected model (NBC) and all bias correction techniques: mean bias-remove technique (U), multiplicative shift technique (M), standardized-reconstruction technique (Z), regression technique (R), along with observation (Y) and the graph shows interannual variability of rainfall where EM is NBC.

3.2 Standard Deviation:

It is observed that the standard deviation of NBC is only 0.25 mm day^{-1} while the observed standard deviation is 0.75mm/day. This reflects that the interannual variability of the model is much less than the observation. This study, therefore, reveals that although the climatology of the all bias corrected methods is the same as observation, their standard deviations differing from each other. The SD of Mean Bias-remove Technique (U) is the same as the raw model and the SD of Multiplicative Shift Technique (M) is also much less than that observed. Among the WOTF technique, only the Standardized Technique (Z) method simulates standard



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deviation (SD) correctly. It may be noted that only this method projects the observations. This may be because the SD is affected by the change of scale due to the transformation in the case of the regression method. Therefore, out of six methods, three methods; Standardized Technique (Z), Quantile Mapping Method (Q) and Principal Component Regression (PCR) simulate the observed interannual variability well.

3.3 Root Mean Square Error (RMSE):

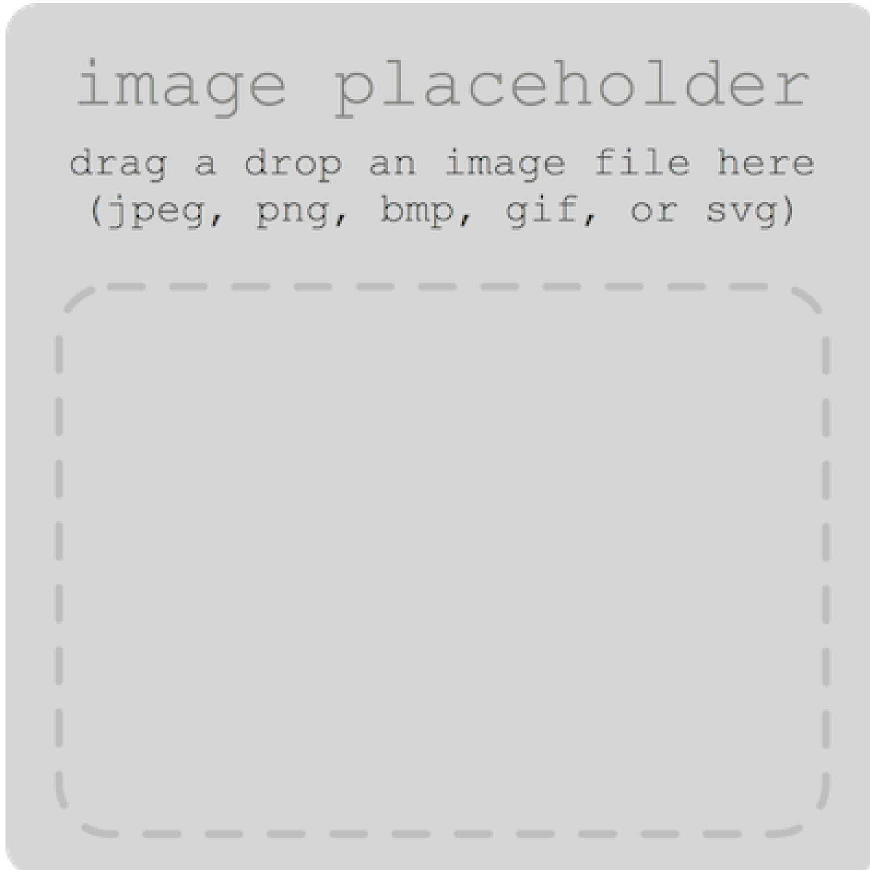
Root mean square error (RMSE) is used to calculate the prevailing inaccuracy of each method explicitly with NBC. It is seen that the RMSE of the NBC is 2.06 mm/day. Among all the techniques, multiplicative method has the least RMSE (0.44mm day^{-1}). It is seen that RMSE of standardized reconstruction technique is higher than other technique. It should be noted that the RMSE only estimates the average error and there is no scope for measuring the relative size of the average difference between model and observation.

3.4. Index of Agreement:

It was stated in Willmott (1981) that although the relative difference measures such as the ratio between RMSE and observed climatology frequently appear in the literature, they have the limitation that they are not bounded and are unstable for very small (near zero) climatology of observation. Willmott (1981) proposed new skill metrics called 'index of agreement (d)', as:

Eq.(11)

Where f_i and O_i is the i $^{\text{th}}$ year forecast and observation and is the observed climatology. This skill metric



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is relative and is bounded between 0 and 1 (0 [?] d [?] 1). The closeness of this index to 1 indicates the efficiency of the model in producing a good forecast. In the present work, this skill metric is calculated for each bias correction method along with NBC. It is seen that NBC has the minimum score 0.37. Among the WOTF methods, Z has highest skill (0.65) and among the WTF method, Q has the highest skill (0.66). Therefore, in the view of index of agreement, both Z and Q methods are most skilful among all six bias correction methods. Values of skill metrics for all the methods are displayed in Table 1.

3.5. Correlation:

One of the main motives of the bias correction is the improvement in correlation between observation and forecast values. Here, NBC has higher correlation (0.1207) than all the techniques. In index of agreement, it is seen that although the standardized reconstruction technique (Z) is the most skillful, but it's correlation is lesser than that of NBC (0.0683).

4. Conclusion:

The above studies show that GCMs comprise biases that are affecting the performance. Here, a comparative study is reported on six different bias correction methods that are applied on the Climate Forecast System (CFS) model for 27 years (1982-2008). Bias corrected rainfall is also tested in extreme years, such as the two deficit years (1987, 2002) and the two excess years (1988, 1994). Among the six methods, three are not using any statistical transformation: mean bias-remove technique (U), multiplicative shift technique (M) and standardized-reconstruction technique (Z). The remaining three methods use statistical transformation:

regression technique (R), quantile-mapping method (Q), principal component regression (PCR). The skills of bias correction techniques only in view of climatology and root mean square error (RMSE) are evaluated. In the present study, for the verification of all such methods and a raw model out puts (NBC) with respect to IMD observation various skill scores have generated. As RMSE only estimates the average error and there is no scope of measuring the relative size of the average difference between model and observation, all the bias correction method were examined by index of agreement (d), which is relative and bounded (0 [?] d [?] 1). The broad conclusions are:

- RMSE is not to be suggested for the evaluation of bias correction method as it is not considering the variation among the rainfall data and it is not a relative measurement. Index of agreement is recommended for evaluating the performance of all methods for simulating of rainfall.
- It is found that both the standardized-reconstruction technique (Z) and quantile mapping method (Q) are equally skillful and the most skillful techniques amongst all the techniques under the present study.
- The quantile mapping method is a sophisticated technique based on statistical transformation, whereas the standardized-reconstruction method is a very simple method, where long term climatology and standard deviation of observed rainfall are projected in the model's anomaly.
- Although the present study is done on a single GCM, the characteristics of bias for all other GCMs are almost the same in the context of the Indian Summer Monsoon rainfall.

Therefore, in general it is concluded that the simple standardized-reconstruction technique is good enough for bias correction for ISMR among all the six bias correction methods.

References:

793–799.

793–799.

Appl. Climatol. 99: 187–192, DOI: 10.1007/S00704-009-0134-9

Barnston AG, Li S, Mason SJ, DeWitt DG, Goddard L, Gong X (2010) Verification of the first eleven years of IRI's seasonal climate forecasts. J Appl Meteorol Climatol 49:493–520. doi:10.1175/2009JAMC2325.1

based on dynamical model output. Weather Forecast. 13: 983–99

correction methods for ensemble streamflow volume forecasts.

daily precipitation in regional climate models over Europe. Theor.

DOI: 10.1029/2009JD012882.

Fan Y, van den Dool H (2011) Bias correction and forecast skill of NCEP GFS ensemble week-1 and week-2 precipitation, 2-m surface Air temperature, and soil moisture forecasts. Weather Forecast. 26:355–370.

Feudale L, Tompkins AM (2011) A simple bias correction technique for modeled monsoon precipitation applied to West Africa. Geophys. Res. Lett. 38: L03803, DOI: 10.1029/2010GL045909.

Feudale L, Tompkins AM. 2011. A simple bias correction technique

Fisher RA (1922) The goodness of fit of regression formulae, and the distribution of regression coefficients. J. R. Stat. Soc. 85(4):597–612

for m odeled monsoon precipitation applied to West Africa. Geophys.

Haerter JO, Hagemann S, Moseley C, Piani C (2011) Climate model bias correction and the role of timescales. Hydrol. Earth Syst. Sci.15: 1065–1079, DOI: 10.5194/hess-15-1065-2011

Hamlet, AF, Huppert D, Lettenmaier DP(2002) Economic value of long-lead stream flow forecasts for Columbia River hydropower, J. Water Resour. Planning and Management-Asce, 128, 91–101, 2002.

Hashino T, Bradley AA, Schwartz SS (2006) Evaluation of bias-correction methods for ensemble stream flow volume forecasts. Hydrol. Earth Syst. Sci. Discuss. 3: 561–594.

Hashino T, Bradley AA, Schwartz SS. 2006. Evaluation of bias-

Hydrol. Earth Syst. Sci. Discuss. 3: 561–594.

Ines AVM, Hansen JW (2006) Bias correction of daily GCM rainfall for crop simulation studies. Agric. For. Meteorol. 138: 44–53.

Kang IS, Lee J, Park CK (2004) The potential predictability of summer means precipitation in a dynamical seasonal prediction system with systematic error correction. J Clim 17:834–844

Kang I-S, Shukla J (2005) Dynamical seasonal prediction and predictability of monsoon. In The Asian Monsoon, Wang B (ed). Praxis Pub. Ltd: Chichester, UK; pp 585–612.

Kharin VV, Zwiers FW (2002) Notes and correspondence: cli-mate predictions with multi-model ensembles. J. Clim. 15:793–799.

Kharin VV, Zwiers FW. 2002. Notes and correspondence: cli-

Kharin VV, Zwiers FW. 2002. Notes and correspondence: cli-

Krishna Kumar K, Hoerling Martin, Rajagopalan Balaji (2005) Advancing dynamical prediction of Indian monsoon rainfall. Geophys Res Lett 32(8):L08704. doi:10.1029/2004GL021979

Li H, Sheffield J, Wood EF (2010) Bias correction of monthly precipitation and temperature fields from the IPCC ARC models using equidistant quantile matching. J. Geophys. Res. 115: D10101,DOI: 10.1029/2009JD012882.

Li H, Sheffield J, Wood EF. 2010. Bias correction of monthly

mate predictions with multi-model ensembles. J. Clim. 15:

mate predictions with multi-model ensembles. J. Clim. 15:

Pan J, van den Dool H (1998) Extended-range probability forecasts based on dynamical model output. Weather Forecast. 13: 983–996

Pan J, van den Dool H. 1998. Extended-range probability forecasts

Piani C, Haerter JO, Coppola E (2009) Statistical bias correction for daily precipitation in regional climate models over Europe. Theor. Appl. Climatol. 99: 187–192, DOI: 10.1007/S00704-009-0134-9

Piani C, Haerter JO, Coppola E. 2009. Statistical bias correction for

precipitation and temperature fields from the IPCC ARC models

Res. Lett. 38: L03803, DOI: 10.1029/2010GL045909.

Sajani S, Nakazawa T, Kitoh A, Rajendran K (2007) Ensemble simulation of Indian summer monsoon rainfall by an atmospheric general circulation model. J. Meteorol. Soc. Jpn., Ser. II 85:213–231.

D10101,

Wang B, Ding Q, Fu X, Kang I-S, Jin K, Shukla J, Doblas-Reyes F (2005) Fundamental challenge in simulation and prediction of summer monsoon rainfall. Geophysical Research Letters 32: L15711, DOI: 10.1029/2005GL022734.

Willmott CJ (1981) On the validation of models. Phys Geogr 2:184–194

Wood AW, Leung LR, Sridhar V, Letternmaier DP (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Climate Change 62: 189–216.