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Hydrology and Earth System Sciences
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Discussions

Interactive comment on "Selection of multi-model ensemble of GCMs for the simulation of precipitation based on spatial assessment metrics" *by* K. Ahmed et al.

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Comment This article proposes an ensemble of GCM model for simulation of precipitation based on spatial assessment metrics. The article presents original research works and outputs. The work is relevant to the interests of the readership of HESS and is well-written. However, there are few issues that need to be addressed. Therefore, authors are encouraged to revise the manuscript accordingly.

Reply Thanks for your highly constructive comments on our manuscript. The manuscript has now been revised according to the comments. The details of the revisions made are given under each comment. Revisions are marked in Red.

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Comment 1 In Section 3, authors introduce different GCM performance assessment metrics. For almost all parameters except Kling-Gupta, the range of the metric and the meaning of the extreme values are elaborated. To be consistent, it is recommended to revise section 3.1.6 accordingly.

Reply Thanks for your suggestion. We have now defined the range of KGE as below. "In the present study, KGE was calculated between historical observed data and GCM simulated data using Eq. (12). KGE values can range between –infinity to 1, where values closer to 1 are preferred."

Comment 2 In section 3.3, it is highlighted that the RM values for annual, monsoon, and winter precipitations are averaged to derive overall rank for each GCM. Does this approach flatten the effect of extreme cases? Was it necessary to average them? How were the individual rankings? Authors need to explain the impact of this approach on their final conclusion.

Reply Thank you very much for this interesting comment. In the original manuscript, in order to derive an overall rank for each GCM, RM values corresponding to annual, monsoon and winter precipitation were first averaged and then based on the average of RM values an overall rank was assigned to each GCM. This procedure helped in assigning one single rank to each GCM while taking into account precipitation for annual, monsoon, and winter seasons all together. Following your above comment, in the revised manuscript, we ranked each GCM for each season (i.e. annual, monsoon, winter, pre-monsoon, and post-monsoon precipitation) to derive ranks for each variable (precipitation, maximum and minimum temperature) separately by applying comprehensive rating metric. Later, comprehensive rating metric was again applied on precipitation, maximum and minimum temperature ranks to derive an overall rank of GCMs for the whole study area. This procedure helps us to avoid averaging. The obtained results are discussed in section 4.3 as below.

4.3 Overall Ranks of GCMs for Precipitation, Maximum Temperature and Minimum

Temperature The application of various evaluation metrics has yielded different ranks for the same GCM (Ahmadalipour et al., 2017;Raju et al., 2017). The ranks attained by GCMs corresponding to different metrics and seasons (annual, monsoon, winter, pre-monsoon and post-monsoon) were used to calculate the RM values for each GCM. The ranks of GCMs for P, Tmax and Tmin are presented in Table 4 along with the RM values. As seen in Table 4, EC-EARTH, BCC-CSM1.1 (m) and CSIRO-Mk3-6-0 were the most skillful GCMs in reproducing the spatial characteristics of P, Tmax and Tmin respectively. On the other hand, IPSL-CM5B-LR, CMCC-CM, and INMCM4 displayed the least skill in reproducing the spatial characteristics of P, Tmax and Tmin respectively.

Table 4 in the supplement file

The better performance of EC-EARTH, BCC-CSM1.1 (m) and CSIRO-Mk3-6-0 in simulating P, Tmax and Tmin over Indo-Pak sub-continent has also been reported in several past studies. Latif et al. (2018) reported the relatively better performance of EC-EARTH, and BCC-CSM1.1 (m) out of 36 CMIP5 GCMs in simulating precipitation over Indo-Pakistan sub-continent based on spatial correlation. Rehman et al. (2018) conducted a study to assess the performance of CMIP5 GCMs in simulating the mean precipitation and temperature over south Asia. The study reported the better performance of EC-EARTH in simulating precipitation and CSIRO-Mk3-6-0 in simulating temperature. Khan et al. (2018) assessed the performance of 31 CMIP5 GCMs in simulating the mean precipitation and temperature over Pakistan using multiple daily gridded datasets and identified EC-EARTH as the best GCM for simulating precipitation and CSIRO-Mk3-6-0 for simulating temperature. Better performance of CSIRO-Mk3-6-0 in simulating maximum and minimum temperature is also reported in the study by (Ahmed et al., 2019b).

Regarding the issue of deriving rank based on average of RM values (given in the original manuscript) and overall ranks based on individual ranks; a comparison was made. The comparison of overall ranks obtained with the above two approaches is shown in Table below (not included in the manuscript). As seen in Table below, it was understood that the differences between the overall ranks derived based on; average of RM values and overall ranks is mostly quite small. Therefore, it can be stated that either the overall ranks can be derived based on average of RM values or individual ranks. However, derivation of overall ranks based on ranks of individual variable is relatively simple and hence recommended.

The 2nd Table in the Supplement file.

Comment 3 It is needed to give some background knowledge about Random Forest method. Why is it selected? It is needed to give some reasoning for this selection. Also in the results and discussion, more explanation is needed for this method. Reply Thank you very much for this comment. We have now added a new sub-section covering the information related to Random Forest algorithm as show below. . 3.5.2 Random Forest (RF) Random Forest (RF) algorithm (Breiman, 2001) was used in the calculation of the mean time series of P, Tmax and Tmin corresponding to an MME of four top ranked GCMs. RF is a relatively new machine learning algorithm widely used in modelling non-linear relationships between predictors and predictands (Ahmed et al., 2019a). RF algorithm is found to perform well with spatial data sets and less prone to over-fitting (Folberth et al., 2019). Most importantly Folberth et al. (2019) reported that RF is less sensitive to multivariate correlation. RF is an ensemble technique where regression is done using multiple decision trees. RF algorithm uses the following steps in regression. A bootstrap resampling method is used to select sample sets from training data. Classification And Regression Tree (CART) technique is used to develop unpruned trees using the bootstrap sample. A large number of trees are developed with the samples selected repetitively from training data so that all training data have equal probability of selection. A regression model is fitted for all the trees and the performance of each tree is assessed. Ensemble prediction is estimated by averaging the predictions of all trees which is considered as the final prediction. Wang et al. (2017) and He et al. (2016) reported that the performance of RF varies with the number of trees (ntree) and the number of variables randomly sampled at each split in developing the trees (mtry). It was observed that RF performance increases with the increase in ntree. However, in the present study the performance was not found to increase significantly in term of root mean square error when the ntree was greater than 500. Therefore, ntree was set to 500 while the mtry was set to p/3 where p is the number of variables (i.e. GCMs) used for developing RF-based MME. The MME prediction can be improved by assigning larger weight to the GCMs which show better performance (Sa'adi et al., 2017). RF regression models developed using historical P, Tmax and Tmin simulations of GCMs as independent variable and historical observed P, Tmax and Tmin as dependent variable provide weights to the GCMs according to their ability to simulate historical observed P, Tmax and Tmin. The "Random Forest" package written in R programming language was employed in this study for developing RF-based MMEs. RF-based MMEs were calibrated with the first 70% of the data and validated with the rest of the data.

Comment 4 Section 4.1, it is suggested to present NRMSE formula. Reply Thank you very much for your suggestion. We have now added a sub-section entitled "Accuracy Assessment of Gridded Precipitation Data" under the method section 3.1 and provided details on NRMSE and md. 3.1 Accuracy Assessment of Gridded Precipitation and Temperature Data The accuracy of gridded GPCC precipitation data and CRU temperature data was assessed by comparing them with observed station data using NRMSE and md. NRMSE is a non-dimensional form of Root Mean Square Error (RMSE) which is derived by normalizing RMSE by variance of observations. NRMSE is more reliable than RMSE in comparing model performance when the model outputs are in different units or the same unit but with different orders of magnitude (Willmott, 1982). NRMSE can have any positive value, however values closer to 0 are preferred as they denote smaller errors (Chen and Liu, 2012). In this study, NRMSE was calculated Eq. 1.

NRMSE=( )/(x_max-x_min) (1) Where xsim,i and xobs,i refer to the ith value in the gridded and observed time series of the climate variable (i.e. precipitation or temperature)

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respectively, and N is the number of data points in each time series.

The ‘md’ shown in Eq. 2 is widely used to estimate the agreement between observed and gridded data of climate variables (Noor et al., 2019;Ahmed et al., 2019a). It varies between 0 (no agreement) and 1 (perfect agreement) (Willmott, 1981).

(2)

Where xsim,i and xobs,i are the ith data point in the gridded data and observed data series of a climate variable.

Comment 5 To have a better understanding about the site, it would be good to add the location of stations on the map. Reply Thank you very much for your suggestion. We have revised Figure 1 and included the locations of the stations. Also, we have provided the names of stations in Table 2.

Figure 1 in the Supplement file.

Table 2 in the Supplement file.

Comment 6 It is also recommended to highlight the limitations of the study in the discussion part Reply Thanks for your suggestion. We have now added the following paragraph to the manuscript to highlight the limitations of this study and recommendation for future work. “In this study performance of GCMs was assessed based on their ability to simulate past observed P, Tmax and Tmin and hence the best performing GCMs were identified and used for the development of MMEs. However, it is found that past and future climate may have a weak association hence it is not necessary that if a GCM performs well in the past will give reliable results in future (Knutti et al., 2010). In other words, the best GCMs selected for the MMEs considering their ability to simulate past climate may not be the best in the future under changing climate (Ruane and McDermid, 2017;Ahmed et al., 2019b). This is due to the large uncertainties associated with GHG emission scenarios and GCMs. As a solution to this limitation, Salman et al. (2018) selected an ensemble of GCMs based on past performance as well as the degree of agreement between their future projections. The study detailed in the present manuscript can be repeated in future to select GCMs considering their past performance and the degree of agreement in their future projections. In the present study, the MME of P, Tmax and Tmin were developed by considering top four ranked GCMs. In the past, MMEs were developed considering 3 to 10 top ranked GCMs. However, none of the study showed the performance of MME by varying the number of GCMs in MME. The performance of an MME can be sensitive to the choice of the number of GCMs. Hence, in future, a study should be conducted to investigate the impact of the number of GCMs used for the development of the MME. Only RF algorithm was used in this study for the development of MMEs. Other machine learning algorithms (e.g. Artificial Neural Networks, Support Vector Machine, Relevance Vector Machine, K-nearest neigbour, Extreme Learning method) can also be used for the development of MMEs. A comparison of the performance of MMEs developed with different machine learning algorithms can assist in identification of pros and cons of different algorithms in relation to development of MMEs. In the present study, GCM ranking and MME development was conducted only considering P, Tmax and Tmin pertaining to annual, monsoon, winter, pre-monsoon and post-monsoon seasons. However, several studies reported that the ranking of GCMs based on different climate variables may assist in the identification of a more dependable set of GCMs for ensemble generation (Johnson and Sharma, 2012;Xuan et al., 2017). In future, the ranking of GCMs can be conducted considering several climate variables (e.g. precipitation, mean temperature, maximum temperature, minimum temperature, wind speed, evapotranspiration and solar radiation)."

Comment 7 For figures 4, 5, and 7 a performance measure such as r-squared is needed for each scatter plot of observed vs simulated data points. Reply Thanks for your suggestion. We have indicated the performance of MMEs in terms of the modified index of agreement (md) in all plots in Figures 4, 5 and 7 as shown below.

Figure 4 in the Supplement file.

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Figure 5 in the Supplement file.

Figure 7 in the Supplement file.

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Please also note the supplement to this comment:
https://www.hydrol-earth-syst-sci-discuss.net/hess-2018-585/hess-2018-585-AC2-supplement.pdf

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