RANKING OF CMIP5 CLIMATE MODELS FOR STATISTICAL DOWNSCALING FOR UPPER GODAVARI RIVER BASIN

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Abstract: In this study, 15 Coupled Model Intercomparison Project-5-based global climate models (CMIP5) are explored to evaluate the performance of precipitation simulations for the Upper Godavari Basin. The study used observed rainfall and model historical rainfall from 1961-2005.Four performance indicators were used for evaluating the GCMs and these indicators are correlation coefficient (CC), normalized root mean square deviation (NRMSD), absolute normalized mean biased deviation (ANMBD) and nash Sutcliffe model efficiency (NSE). Entropy was used for calculating the weights of the four performance indicators. However CRITIC method was also used for determining the weights of performance indicators. Compromise programming (CP) technique is employed to rank the GCMs based on the distance measure technique Out of the 15 models selected, the GFDL-CM3 model, occupies the first rank for the Upper Godavari river basin in both the weight determination method.
Keywords: *CMIP5; Entropy method; CRITIC method; Compromise programming*

1. INTRODUCTION

Changes in the concentration of greenhouse gases and in the radiative balance of the atmosphere cause corresponding changes in temperature and precipitation patterns. The numerical tools indicating the physical processes of land, ocean and atmosphere for simulating the impacts at regional and hydro climatological studies are global circulation models. The accuracy of GCMs decreases when it is used at finer scales (Xu 1999). The main reason for this decrease in accuracy is the uncertainties like variability in simulations, downscaling to regional or local levels. Therefore it is important to evaluate different GCMs to confirm the extent to which they can reproduce the observed variations in the hydroclimatological variables. To identify GCMs performance, various performance measures have been developed (Gleckler et al. 2008; Knutti et al. 2010; Johnson and Sharma 2009; Fordham et al. 2011; Pitman et al. 2012). Four performance indicators are used for evaluating the ability of 15 GCMs from CMIP5. CMIP5 consists of a more diverse set of GCMs with elements such as ice sheets, dynamic vegetation, aerosols as compared to CMIP3. Fifteen selected GCMs for this study are ACCESS 1.0, ACCESS 1.3, CSIRO-Mk3.6, CNRM-CM5, CanESM2, FGOALS-s2, FIO-ESM, GFDL-CM3, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-AO, MIROC5, MIROC-ESM, IPSL-CM5A-MR and NorESM1-M. Entropy method is applied to calculate the weight of four indicators employed. To rank the GCMs, a distance-based decision-making technique called compromise programming is employed. Weights obtained by the entropy method are the inputs to the compromise programming. Compromise Programming (CP) has the skill to identify the closest ideal and optimal solution compared to other methods of multi criteria-decision making (Salman et al. 2018b; Srinivasa Raju et al. 2016). Ranking is done to determine which model is suitable for the study area for the projection of future rainfall. The objective of this study is to evaluate different CMIP5 models based on their performance indicators and also to rank them for the future projection of rainfall for the study area.

2. METHODOLOGY

2.1 Study Area

Godavari is the second largest river after Ganga. The basin lies between latitudes 16˚16'0"N and 23˚43'N longitudes 73˚26'E and 83˚07'E. The basin extends over an area of 312,813 km2, which is nearly 10% of the total geographical area of the country. The Godavari has been ranked 34thand 32nd in terms of the catchment area and discharge respectively, among the 60 major rivers of the world. The Godavari originates in the Western Ghats of central India near Nashik in Maharashtra, 80 km from the Arabian Sea. It flows for 1,465 km, first eastwards across the Deccan Plateau then turns southeast, entering the West Godavari district and East Godavari district of Andhra Pradesh, until it splits into two distributaries that widen into a large river delta at Sir Arthur Cotton Barrage in Rajamahendravaram and flow into the Bay of Bengal. But in this study, only the Upper Godavari River basin is taken into consideration. This region is enclosed between 73° to 75.75° E longitude and 19° to 20.75°N latitude. The Upper Godavari basin occupies an area of 21774km^2.The mean monthly maximum temperature in the upper Godavari basin varies from 29.64 to 38.6℃. The maximum annual daily rainfall obtained in the Upper Godavari River basin during the period 1961-2005 is 134mm according to the data provided by Indian Meteorological Department, Pune.

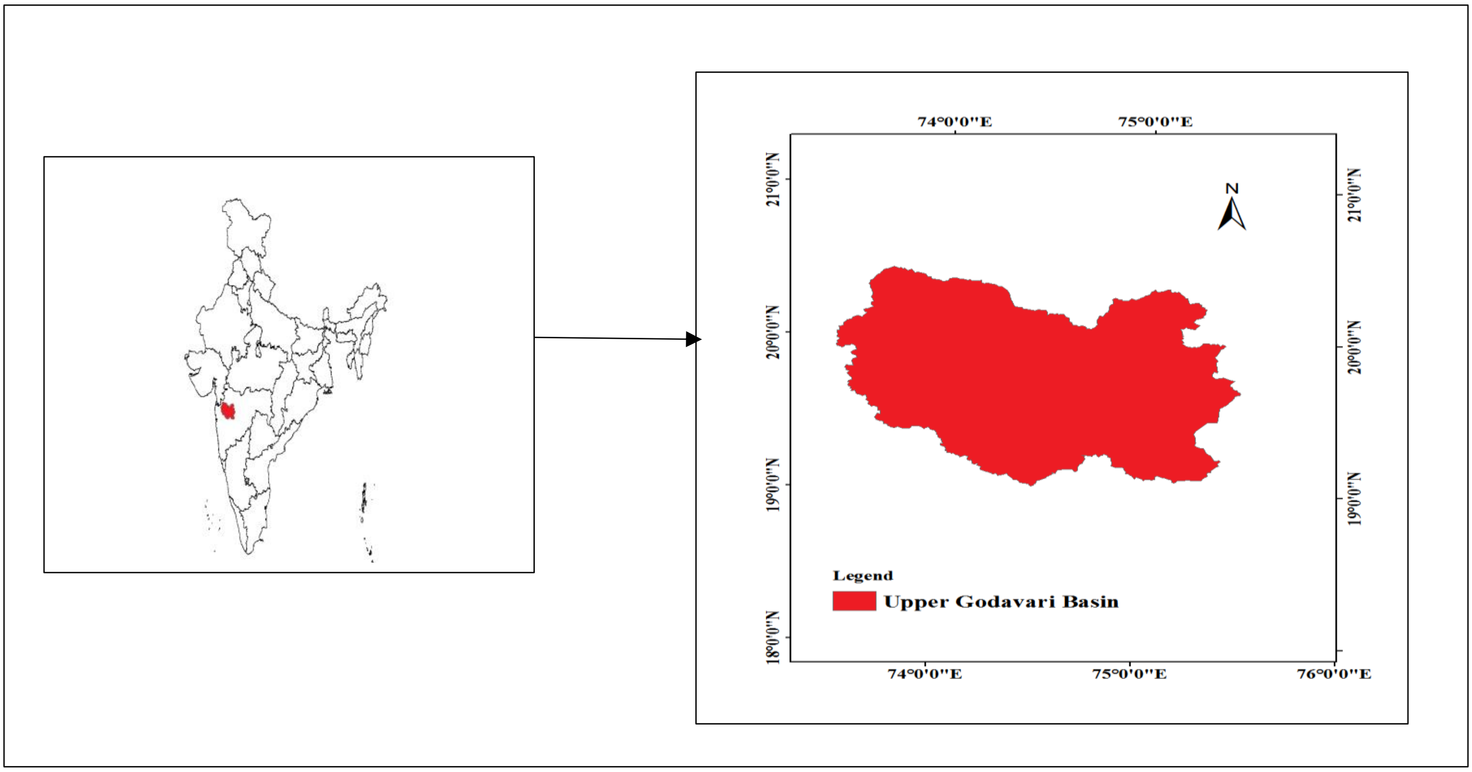

Fig.1 Location map of Upper Godavari River Basin

2.2 Data Used

Gridded rainfall data for the Upper Godavari River basin from 1961-2005 was obtained from Indian Meteorological Department, Pune. 15 dataset models of CMIP5 were considered for evaluation and these models were selected on the basis that it has historic data of precipitation from 1961-2005.

2.3 Performance Indicators

A performance indicator is a quantifiable measure to determine how GCMs simulate the observed data (Raju et al 2016). Four indicators, namely, correlation coefficient (CC), normalized root mean square deviation (NRMSD), absolute normalized mean biased deviation (ANMBD) and nash Sutcliffe model efficiency (NSE) are considered among the numerous performance indicators available (Wilks 2011).Correlation coefficient is based on the strength of relationship between observed and GCM simulated values. Its value can range from -1 to 1. Negative value indicates negative correlation and positive value indicate a positive correlation. CC values near 1 indicate good model performance.

$$CC = \frac{\sum_{i=1}^{n}(x_i - x_{av})(y_i - y_{av})}{(n-1)S_x S_y} \quad (1)$$

Where x_i and y_i are observed and simulated values, x_{av} and y_{av} are the means of observed and simulated values, s_x and s_y are the standard deviations of observed and simulated values and n is the number of observations.

Normalized root mean square deviation (NRMSD) is a measure of difference between observed values and simulated values by GCMs.

$$NRMSD = \frac{\sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_i - y_i)^2}}{x_{av}} \quad (2)$$

The smaller the value of NRMSD, preferably zero, better is the performance of the model.

Absolute Normalized Mean Biased Deviation (ANMBD) is computed by using the following equations.

$$ANMBD = \left|\frac{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - x_i)}{x_{av}}\right| \quad (3)$$

Here also the smaller value indicate the better performance of model.

Nash Sutcliffe Model Efficiency (NSE) determines the relative magnitude of variance of residues and measured data. It ranges from -∞ to 1 with 1 being the optimal value. The values below 0 represent unacceptable performance whereas values within 0 to 1 indicate acceptable levels of performance of model.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - x_{av})^2} \quad (4)$$

2.4 Techniques Employed

2.4.1. Entropy Method

Analysis by entropy method is based on the amount of information available and its relationship with the importance of the indicators. Entropy method measures the weight of each performance indicator separately and find the difference among the sets of data in payoff matrix. Weights calculated by this entropy method are relative importance of the performance indicators metrics for ranking models based on compromise programming. The entropy of the matrix (E_z) is given by,

$$E_z = \frac{-1}{ln(x)}\sum_{i=1}^{x} p_{iz} ln(p_{iz}) \quad (5)$$

p_{iz} is payoff matrix, E_z is entropy of metric of i is equal to number of models ranging from 1 to x.

2.4.1.1 Degree of diversification

Degree of diversification (D_Z) is the information by the outcome of the criterion z and is expressed as follows,

$$D_z = 1 - E_z \quad (6)$$

2.4.1.2 Normalizing weights of performance indicators

Assigned weights of the performance indicators obtained by the entropy method w_z is expressed as follows,

$$w_z = \frac{D_z}{\sum_{z=1}^{Z} D_z} \quad (7)$$

2.4.2 Compromise programming

Compromise programming is based on the minimum distance of a GCM from an ideal in the available set (Zeleney 1982). Distance measure L_p metric is defined as follows:

$$L_p(a) = [\sum_{z=1}^{Z} w_z{}^p |f_z{}^* - f_z(a)|^p]^{\frac{1}{p}} \quad (8)$$

Where indicator z=1, 2,.. Z; $L_p(a)$ = L_p metric for GCM a for the chosen value of parameter p; $f_z(a)$ = normalized value of indicator z for GCM a; $f_z{}^*$= normalized ideal value of indicator z; w_z = weight of indicator z obtained from entropy method; p = Parameter and the value of p is 1 for linear and 2 for squared Euclidean distance measure.

3. RESULTS AND DISCUSSION

Upper Godavari basin region is enclosed between 73° to 75.75° E longitude and 19° to 20.75°N latitude. Since most of the GCM models are of 2.5°*2.5° resolution it is difficult to do the analysis for one grid point in this study area so average value of all the grid points covering this region is taken for the present study but later the study will extend for the entire Godavari.

3.1 Entropy and compromise programming methods

Among the four performance indicators, NSE is given high importance (0.7119), which means that its effect on GCM ranking is very significant followed by ANMBD (0.1924), CC (0.0709) and NRMSD (0.0246). Combined contribution of ANMBD, CC and NRMSD is less than 30% whereas the combined contribution of correlation coefficient and normalized root mean square deviation is less than 10%. To differentiate the weights of the indicators, entropy method is used which give different weight for different performance indicators instead of providing equal weights which ultimately affects the ranking of GCM. Table 1 shows the weight in percentage obtained by entropy method for the four performance indicators.

Table 1 Distribution of weights obtained by entropy method

Performance indicators	CC	NRMSE	ANMBD	NSE
Weight (%)	7	2	19	72

Weight obtained by entropy method is given as the input to the compromise programing. Table 2 represents the values of L_p metric and ranking for 15 GCMs for p value equal to 2. While inferring ranking even a small change in the value of L_p metric is accounted. For obtaining the rank for GCMs, the minimum value of the L_p metric is considered. It is observed that the value of L_p metric is varying between 0.1226 (first rank) and 2.3878 (last rank) over 15 ranks. GFDL-CM3, CanESM2 and CNRM-CM5 occupy the first three positions with L_p metric values of 0.1226,0.1262 and 0.1829 respectively which indicates that these GCMs can be explored for further process such as downscaling and hydrologic modelling studies. ACCESS 1.0 and GFDL-ESM2G occupied fourth and fifth position with L_p metric values of o.2230 and 0.2769 respectively. FGOALS- s2 and MIROC-ESM occupied 14^{th} and 15^{th} positions with L_p metric values 1.6935 and 2.3878 respectively.GFDL-CM3, GFDL-ESM2G and GFDL-ESM2M are the GCMs developed by the same organization, Geophysical Fluid Dynamics Laboratory. However there ranking positions are 1^{st},5^{th} and 7^{th} respectively. Thus, it may be noticed that mostly GCMs are showing different L_p metric values even though they are developed by the same modelling center.

Table 2 Values of performance indicators, L_p metric value and ranking pattern for GCMs (entropy method)

Model name	CC	NRMSD	ANMBD	NSE	L_p metric	Rank
GFDL-CM3	0.7041	1.2000	0.2124	0.2258	0.1226	1
CanESM2	0.5816	1.2050	0.1567	0.2193	0.1262	2
CNRM-CM5	0.6540	1.2659	0.0984	0.1384	0.1829	3
ACCESS1.0	0.5429	1.2873	0.5630	0.1090	0.2230	4
GFDL-ESM2G	0.6842	1.3587	0.2116	0.0076	0.2769	5
HadGEM2-AO	0.5018	1.3537	0.6613	0.0148	0.2922	6
GFDL-ESM2M	0.6488	1.3891	0.1671	-0.0375	0.3084	7
NorESM1-M	0.6368	1.4139	0.1753	-0.0747	0.3350	8
ACCESS 1.3	0.4396	1.4737	0.7922	-0.1676	0.4230	9
CSIRO-Mk3.6	0.2264	1.6304	0.9335	-0.4291	0.6097	10
IPSL-CM5A-MR	0.0072	1.7694	0.2818	-0.6831	0.7704	11
MIROC5	0.6725	1.8839	0.6808	-0.9081	0.9348	12
FIO-ESM	0.6809	1.8966	0.6273	-0.9339	0.9519	13
FGOALS-s2	0.6378	2.3528	0.7705	-1.9760	1.6935	14
MIROC-ESM	0.7521	2.7059	1.5085	-2.9364	2.3878	15

3.2. CRITIC and compromise programming method

Criteria Importance through Intercriteria Correlation (CRITIC) method was used to determine the weights of the indicators. Weights obtained by the CRITIC method for performance indicators are entirely different from that of entropy method. Among the four performance indicators, CC is given high importance (0.4502) followed by ANMBD (0.19609), NSE (0.19028) and NRMSD (0.18861).In this method the combined contribution of ANMBD, NSE and NRMSD is more than the weight obtained for CC. Weight obtained by this method is given as the input to the compromise programming and the values of L_p metric is found out. In this case the value of L_p metric is varying between 0.0442(first rank) to 0.7476(last rank). GFDL-CM3, CNRM-CM5 and CanESM2 occupied the first, second and third position respectively. GFDL-ESM2M and GFDL-ESM2G occupy the fourth and fifth position whereas FGOALS-s2 and MIROC-ESM occupied the $14^{th}$and 15^{th} position respectively. Table 3 represents the values of L_p metric and ranking for 15 GCMs for p value equal to 2 obtained by CRITIC method. In both the weight determination method, GFDL-CM3 occupies the first position but there is a slight change in second and third position. In entropy method CanESM2 occupied the second position whereas in CRITIC method, CNRM-CM5 occupied the second position and CanESM2 occupied the third position.

Table 3 Values of performance indicators, L_p metric value and ranking pattern for GCMs (CRITIC method)

Model name	CC	NRMSD	ANMBD	NSE	L_p metric	Rank
GFDL-CM3	0.7041	1.2000	0.2124	0.2258	0.0442	1
CNRM-CM5	0.6540	1.2659	0.0984	0.1384	0.0654	2
CanESM2	0.5816	1.2050	0.1567	0.2193	0.0806	3
GFDL-ESM2G	0.6842	1.3587	0.2116	0.0076	0.0875	4
GFDL-ESM2M	0.6488	1.3891	0.1671	-0.0375	0.1008	5
NorESM1-M	0.6368	1.4139	0.1753	-0.0747	0.1107	6
ACCESS1.0	0.5429	1.2873	0.5630	0.1090	0.1394	7
HadGEM2-AO	0.5018	1.3537	0.6613	0.0148	0.1720	8
ACCESS 1.3	0.4396	1.4737	0.7922	-0.1676	0.2242	9
MIROC5	0.6725	1.8839	0.6808	-0.9081	0.3038	10
FIO-ESM	0.6809	1.8966	0.6273	-0.9339	0.3048	11
CSIRO-Mk3.6	0.2264	1.6304	0.9335	-0.4291	0.3285	12
IPSL-CM5A-MR	0.0072	1.7694	0.2818	-0.6831	0.3939	13

FGOALS-s2	0.6378	2.3528	0.7705	-1.9760	0.5202	14
MIROC-ESM	0.7521	2.7059	1.5085	-2.9364	0.7476	15

4. CONCLUSION

Four performance indicators were used to rank 15 CMIP5 climate models based on the simulated and observed rainfall for Upper Godavari basin. Weights between different performance indicators were determined by Entropy and CRITIC method. In entropy method, NSE is given high importance whereas in CRITIC method, CC is given high importance. GFDL-CM3 model occupied the first position based on L_p metric value in both the weight determination methods among the 15 GCMs selected for the study area. GFDL-CM3 is followed by CanESM2 and CNRM-CM5 in both methods. Here only 15 models are taken into account but the study can be extended for the remaining CMIP5 models and the study area can also be extended so as to evaluate the ability of models at each grid point.

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