Assessment of CMIP5 multimodel mean for the historical climate of Africa

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Abstract
The fidelity of 28 CMIP5 models and their multimodel mean (MMM) in simulating the historical climate of Africa is assessed in this study. For the historical period of 1975–2005, the spatial distribution of the seasonal precipitation is simulated with pattern correlation coefficients (PCCs) of 0.91, 0.95, 0.94, and 0.95 for March–May (MAM), June–August (JJA), September–November (SON), and December–February (DJF) seasons, respectively, when compared with the CRU data. For the surface temperature, the PCCs are 0.96, 0.98, 0.83, and 0.97, respectively, for the four seasons mentioned in the preceding. The root mean square error (RMSE) for the precipitation are 0.86, 0.77, 0.97, and 1.05 mm day\(^{-1}\) for the MAM, JJA, SON, and DJF seasons, respectively, whereas for the temperature, the respective values are 1.64, 1.28, 1.68, and 1.87°C. The study also assesses the performance of the models over four sub-regions of Africa, viz. North, South, East, and West Africa. The observational trends show large spatial heterogeneity in warming for each season. The MMM does not show the strong warming over Africa and simulate generally a weak warming over most of the region. The MMM fails to capture the sign and magnitude of the observed precipitation trends.

KEYWORDS
Africa, CMIP5, model fidelity, precipitation, surface temperatures

1 | INTRODUCTION

The precipitation plays a critical role in the hydrologic cycle over the African continent (Sylla et al., 2010). Many studies have examined the response of precipitation over the African region under the global climate change (Biasutti et al., 2008, 2009; Monerie et al., 2012a, 2012b). The extreme weather conditions are noted to increase over the major part of African continent (Nicholson, 2013) and frequent changes are noted in wet and dry conditions (Fontaine et al., 2011; Fotso-Ngumo et al., 2018; Ongoma et al., 2018). This year-to-year precipitation variance tends to change the populace lifestyles and activities, such as changes in the areas under cultivation. Therefore, it is important to assess the past changes in precipitation and predict the future intensity and variability.

During the last four decades, general circulation models (GCMs) have been substantially utilized to project the future precipitation (IPCC, 2007) over Africa, however, the fundamental concern is how to gauge the reliability of these model projections. Vizy et al. (2013) have examined the simulation of temperature and precipitation in a regional climate model and five Climate Model Inter-comparison Project 5 (CMIP5) models over the Sahel region. The CMIP5 models were
found to poorly simulate the seasonal cycle of rainfall and the circulation over the northern and sub-Saharan Africa. However, they reported improved agreement among models regarding the precipitation changes as compared to the CMIP3. Brands et al. (2013) compared the output of seven Earth System Models (ESMs) from CMIP5 over Africa and reported that many of the errors that were noted in CMIP3 GCMs (e.g., cold bias in middle troposphere temperatures over Africa) still persist in CMIP5 ESMs. Mehran and Phillips (2014) have cross-validated precipitation simulated by 34 CMIP5 models using Global Precipitation Climatology Project (GPCP) data, demonstrating that almost all CMIP5 simulations are in good concurrence with GPCP spatial patterns over most of the areas of African continent. However, the reproduction of precipitation pattern over arid and some continental regions was found to be dubious. Aloysius et al. (2016) compared the historical run of 25 CMIP5 models with observational precipitation and temperature over central Africa and showed that the CMIP5 models simulate temperature better than the precipitation. In their study, many models were not able to simulate the seasonality, spatial patterns, and magnitude of precipitation. In a recent paper, Fotso-Ngumo et al. (2018) have examined the performance of 20 CMIP5 models for precipitation over Central Africa and showed that only 11 models out of 20 performs satisfactorily. They also noted that the ensemble mean rainfall is generally lower than the TRMM and GPCP for 1998–2005. For the western and Southern African also, the MMM is noted to capture the broad distribution of precipitation with some degree of success (Kay and Washington, 2008).

Brown et al. (2010) have shown that the models successfully depicted the synoptic regimes and attributed the eccentricities in precipitation simulations to the difficulty encountered while simulating the precipitation characteristics in various synoptic regimes. These studies did not show the ability of CMIP5 models to capture the spatial distributions of temperature and precipitation for each season. Therefore, in this paper, we examine the simulation of seasonal mean precipitation and temperatures using the MMM of 28 CMIP5 models. We also assess the performance of each individual model to identify the models with the best and worst performance for a given region and season which can be used for climate projections.

For reliable future projections, it is important that the models capture not only the mean climate but also the trends. Li et al. (2016) have noted significant drying trends during 1948–2005 over tropical Africa in observations and showed that the CMIP5 models do not reproduce the trends over this region. Lyon and Vigaud (2017) have noted severe decline of rainfall over the East African region in observations but most models project wet conditions over this region under changing climate. Sylla et al. (2016) examined recent trends in seasonal mean (May–September) temperature and precipitation over West Africa from 1983 to 2010 and showed that the region is warming due to increase in anthropogenic greenhouse gas forcing. They also showed that the Sahel has become wetter whereas a small part of the Gulf of Guinea has become relatively drier. The lower frequency warming trends observed over East Africa is due to modulations of Indo-Pacific Warm Pool heating (Cook and Vizy, 2013). In this paper, in addition to the seasonal mean features, we also revisit the model’s capability to simulate the trends for the period 1975–2005. Section 2 provides the details of the models and observations used in the analysis. The assessment of models is provided in Sections 3 and 4 presents the discussion and conclusion of this study.

### Key findings

- The fidelity of 28 Climate Model Inter-comparison Project 5 (CMIP 5) models and their multimodel mean (MMM) in simulating the historical climate of Africa is assessed.
- The observational trends show large spatial heterogeneity in warming for each season.
- The MMM do not show any strong warming over Africa and simulate a general weak warming over most of the region.
- The MMM fail to capture the sign or magnitude of the observed precipitation trends over Africa.

## 2 DATA AND METHODS

The surface air temperature and precipitation from the CRU (Harris et al., 2014) at 0.5° resolution are used to evaluate the fidelity of 28 CMIP5 models (see Table 1) in simulating the seasonal distribution of precipitation and surface temperature over Africa. CRU is one of the most trustworthy sources of historical observations over Africa (Mitchell and Jones, 2005) and therefore, we use this product for model validation. The historical runs from the CMIP5 models are available from 1850 to 2005. In this paper, we look at the last three decades, that is, 1975–2005, to examine the fidelity of these models for the recent past. The monthly mean precipitation and surface temperature from single ensemble member (r1i1p1) of 28 CMIP5 models are analyzed for the period of 1975–2005. The MMM is calculated by taking the average of the outputs from the selected 28 CMIP5 models. The uncentered pattern correlation coefficient (PCC) and root mean square
errors (RMSE) are computed to evaluate the systematic errors and agreement between models and observations. The PCC is determined to gauge the degree of resemblance between observed and model fields. The linear trends are calculated using least square method and the statistical significance (95% confidence level) is determined by using student’s t-test. The model outputs and observations are bi-linearly interpolated to $0.25^\circ / C_14 \times 0.25^\circ / C_14$ for inter-comparison. The interpolation method used in this study do not have any significant impact on the spatial distribution of climatology, trends, biases or annual cycle. Several past studies have also used bi-linear interpolation and obtained satisfactory results (New et al., 1999; Hempel et al., 2013; Zhao et al., 2015; Li et al., 2016; Fotso-Nguemo et al., 2018; Salunke et al., 2018). Since this paper mainly focuses on the climatological seasonal means, the interpolation has negligible impact on the findings of this paper.

3 | RESULTS

3.1 | Spatial distribution of the climatological means over Africa

Figure 1a, d, g, and j shows the seasonal mean precipitation over Africa for March–May (MAM), June–August (JJA), September–November (SON), and December–February (DJF), respectively from the CRU data. The MMM precipitation distributions for all four seasons are shown in Figure 1b, e, h, and k. The biases in MMMs are shown in Figure 1c, f, i, and l for all four seasons. The spatial

| Table 1 | The CMIP5 models analyzed |
|---------|---------------------------|
| Model name | Country | Model type | Horizontal resolution (lon × lat) | Model vertical levels |
| CESM1-CAM5 | United States | AO | $1.25 \times 0.9$ | 26 |
| CCSM4 | United States | AO | $1.25 \times 0.94$ | 26 |
| CanCM4 | Canada | AO | $2.8 \times 2.8$ | 35 |
| CanESM2 | Canada | ESM | $2.8 \times 2.8$ | 35 |
| CNRM-CM5 | France | AO | $1.4 \times 1.4$ | 31 |
| CSIRO-Mk3.6.0 | Australia | AO | $1.8 \times 1.8$ | 18 |
| EC-EARTH | Europe | AO | $1.125 \times 1.12$ | 62 |
| FGOALS-g2 | China | AO | $2.8 \times 1.6$ | 26 |
| GFDL-CM3 | United States | AO | $2.5 \times 2.0$ | 48 |
| GFDL-ESM2G | United States | ESM | $2.5 \times 2.0$ | 48 |
| GFDL-ESM2M | United States | ESM | $2.5 \times 2.0$ | 48 |
| GISS-E2H | United States | ChemAO | $2.5 \times 2.0$ | 40 |
| GISS-E2R | United States | ChemAO | $2.5 \times 2.0$ | 40 |
| ACCESS1.0 | Australia | AO | $1.875 \times 1.25$ | 38 |
| BCC-CSM1.1 | China | ESM | $2.8 \times 2.8$ | 26 |
| HadCM3 | United Kingdom | AO | $3.75 \times 2.5$ | 19 |
| HadGEM2-CC | United Kingdom | ESM | $1.875 \times 1.25$ | 60 |
| HadGEM2-ES | United Kingdom | ChemESM | $1.875 \times 1.25$ | 60 |
| INM-CM4 | Russia | AO | $2.0 \times 1.5$ | 21 |
| IPSL-CM5A-LR | France | ChemESM | $3.75 \times 1.8$ | 39 |
| IPSL-CM5A-MR | France | ChemESM | $2.5 \times 1.25$ | 39 |
| MIROC4h | Japan | AO | $0.56 \times 0.56$ | 56 |
| MIROC5 | Japan | AO | $1.4 \times 1.4$ | 40 |
| MIROC-ESM | Japan | ESM | $2.8 \times 2.8$ | 80 |
| MIROC-ESM-CHEM | Japan | ChemESM | $2.8 \times 2.8$ | 80 |
| MPI-ESM-LR | Germany | ESM | $1.9 \times 1.9$ | 47 |
| MRI-CGCM3 | Japan | AO | $1.1 \times 1.1$ | 48 |
| NorESM1-M | Norway | ESM | $2.5 \times 1.9$ | 26 |

Note: They are available through the Earth system grid federation archive (ESG, http://cmip-pcmdi.llnl.gov/cmip5) described in Taylor et al. (2012).
distribution of precipitation over Africa is largely affected by the seasonal migration of ITCZ, as can also be seen in the observations. The Congo basin is the wettest region during MAM with large amount of precipitation near the Guinea coast because of vegetation and high convective activity. During JJA, peak precipitation is seen over the coast of West Africa. Past studies have shown that the increase in precipitation over this region is associated with the south-westerly moisture transport from the ocean (Pu and Cook, 2010). During SON, the highest precipitation is noted over the Gulf of Guinea, Congo basin, the southern sector of West Africa and whereas the rest of the Africa is relatively dry. For DJF, the southern Africa receives highest rainfall, which is due to the availability of adequate moisture and stronger summer insolation, which intensify atmospheric convection leading high precipitation over this region (Simon et al., 2015). There are other important mechanisms such as local and remote sea surface temperatures, African easterly jet, low-level jets, topography, SST gradient across latitude, among others that lead to the observed spatial distribution of temperature and precipitation (Nicholson and Dezfuli, 2013; Tierney et al., 2013; Washington et al., 2013; Aloysius et al., 2016; Hua et al., 2016) over Africa.

The CRU and MMM have similar spatial distribution, however, there are differences in the intensity. During MAM, the MMM captures the large-scale distribution of observed precipitation, however, there is a large wet bias over the Equatorial Africa. For MAM, almost half of the models overestimated precipitation over the continent (figure not shown), while most models have great concurrence with observation in the northern and southern parts of the continent. During JJA and SON, the distributions are in fairly good agreement for the northern and southern parts of the continent except over the Gulf of Guinea and the southern part of South Africa during SON. The MMM overestimates the DJF precipitation for 0–30°N latitude band over Africa.

Figure 2 shows the seasonal mean surface temperature over Africa obtained from the CRU data. The MMMs and observations have similar distributions over the African continent for MAM and JJA season except over Central Africa, Ethiopia, and Madagascar. The MMM underestimates the temperature over the northern Africa during MAM. For JJA, the same is observed over Congo basin and West Africa. The MMM overestimates the temperature over the northern and southwestern continental boundaries of Africa. This bias in temperature over the continental boundaries is common in several individual CMIP5 models (figure not shown). For SON, the distribution is in good concurrence with observations across entire Africa but there exist a general cold bias in most of the CMIP5 models. It is clearly observed that MMMs can simulate the distribution of seasonal mean temperature over Africa but the magnitude is relatively less than the observations for most regions and all seasons. These results also agree with Vizy et al. (2013) who found a similar cold bias over Africa in CMIP5 models. Some of the gap between observation and models can be attributed to meridional large-scale temperature gradient and displacement of ITCZ in models (Richter and Xie, 2008), which also leads to increase in rainfall over the Guinea coast and a decrease over the Sahel.

### 3.2 Spatial distribution of trends over Africa

Figure 3a, c, e, and g shows the spatial distribution of trends in precipitation from CRU data for MAM, JJA, SON, and DJF, respectively. The trends in MMMs are shown in Figure 3b, d, f, and h for corresponding seasons. The negative values denote decreasing trends, whereas, the positive values denote increasing trends. The trends that are significant at 95% confidence level are stippled. Figure 3a, c, e, and g show that there is large spatial heterogeneity in the trends. The seasonal precipitation has decreased and increased over the localized regions of the African continent in observations. A general decreasing trend is apparent over the southern Africa during the MAM season (Figure 3a) in observations whereas the MMM fail to capture the reduction in precipitation and shows an overall increasing trend (Figure 3b). The trends in JJA precipitation are also not captured by the MMMs over equatorial Africa. Observations show reduction in precipitation over the mountainous region during SON, and the CMIP5 models partially capture this reduction. The DJF precipitation shows large reduction over southern Africa which is not captured by the MMM. Maidment et al. (2015) have examined the observed changes in precipitation over the African region for 1983–2014 and showed robust regional increase in rainfall over Sahel and South Africa. The increase in Sahel rainfall was attributed to green house gas forcing (Dong and Sutton, 2015), however, the increment noted over the South Africa was attributed to the stronger walker circulation. Over the central Africa, reduction in rainfall was noted which could also be due to the reduction in rain gauge density over this region. The authors have also examined nine CMIP5 models and suggested that the SST patterns and tele-connections play a crucial role in determining the rainfall trends over Africa (Aloysius et al., 2016). In MMMs, the seasonal trends are generally smaller in magnitude than the observations over the Africa continent. Considerable differences in observed and model-simulated trends sign and magnitude are also observed during all seasons. Trends in precipitation are not overall significant except during SON and MAM over equatorial Africa, which could also be due to the lack of observed datasets over these regions (Sylla et al., 2016). The seasonal variability observed in trends could be due to the surface elevation, orography, land-cover, etc. In addition, the physical
FIGURE 1  Climatology of precipitation (mm/day) over Africa for the historical period (1975–2005) from CRU data (1st column), multimodel mean (2nd column), and biases in the multimodel mean with respect to the CRU data for the four seasons: March–April–May (MAM), June–July–August (JJA), September–October–November (SON), and December–January–February (DJF), respectively.
FIGURE 2 Climatology of surface air temperature (°C) over Africa for the historical period (1975–2005) from CRU data (1st column), multimodel mean (2nd column), and biases in the multimodel mean with respect to the CRU data for the four seasons: March–April–May (MAM), June–July–August (JJA), September–October–November (SON), and December–January–February (DJF), respectively.
The processes leading to rainfall during different seasons are quite different which can also have an influence on the distribution of trends. For instance, increase in anthropogenic aerosols over the continent causes the drying trend due to both negative dynamic and thermodynamic effects over the tropical Africa (Kawase et al., 2010).
Figure 4 shows the spatial distribution of trends in temperature over the African continent. Significant warming, with values varying from 0.1 to 2.2°C over the study period of 31 years, is observed over the entire African land. The warming is more pronounced over the northern and southern Africa than the equatorial region for all four seasons. The warming during DJF is relatively less than other seasons of the year. The highest warming is observed over the western Africa during DJF and MAM. Past studies showed that the seasonal cycle of trend is associated to the atmospheric circulation and the Saharan heat low which can also influence the WAM system by increasing the temperature gradient.

In addition, the largest trends occur over southern Africa (during all seasons), North Africa (during MAM, DJF, and JJA) and parts of central Africa (during JJA, SON, and DJF).

The MMMs do not capture the warming intensity or the distribution over most of the African land. The magnitude of warming is relatively higher over the North Africa than the rest of the African region in MMMs. This figure, thus, shows that though the models simulate significant warming over the entire African continent but they do not correctly capture the magnitude or distribution of trends in temperatures. The origin of these errors may be linked to deficiency in the models physics such as the errors in clouds and energy fluxes representation, coupling at the surface and convection at the sub-grid scale, the rough resolution climate models, which is inefficient to simulate the meso-scale convection (Biasutti, 2013) leading biases in both mean climate and trends.

### 3.3 Model performance and errors

The PCC and RMSE are calculated for the MMM as well as individual models for each season in this section. Note that the RMSE and PCC are computed with respect to the temperature and precipitation observations from CRU data. The best (worst) performing models will have the highest (lowest) PCC and the lowest (highest) RMSE. Figure 5 shows the PCC and RMSE for temperature and precipitation over the African region for all four seasons. For precipitation (as shown in Table S5), most models have PCC > 0.8 suggesting satisfactory simulation of spatial distribution.

Most models have higher RMSE in MAM and SON than JJA. The MIROC-ESM model has the highest RMSE for all the three seasons: 2.02 mm/day for MAM, 2.28 mm/day for JJA and 2.26 mm/day for SON. For JJA, two models (GFDL-CM3 and MPI-ESM-LR) exhibit the best performance with RMSE lower than 1 mm/day whereas the MIROC5 shows worst performance with lowest PCC and high RMSE. For SON, the models Can-CM4, EC-EARTH, MPI-ESM-LR and MRI-CGCM3 have RMSE lower than 1 mm/day. For DJF season, FGOALS-g2 model performs best with PCC and RMSE of 0.95 and 0.82 mm/day, respectively. Around 60% of the models have PCC higher than 0.9 for this season. The NorESM1-M shows the worst performance during DJF with PCC and RMSE of 0.81 and 2.5 mm/day, respectively. Models which perform best are HadGEM2-ES (MAM), GFDL-CM3 and MPI-ESM-LR (for JJA), EC-EARTH (for SON) and FGOALS-g2 (for DJF) while the models with worst performance are MIROC5 (for MAM, JJA and SON) and NorESM1-M (for DJF).

Most of the models can simulate spatial patterns of surface temperature (as shown in Table S10) quite satisfactorily (Figure 5, 2nd column), with 18 models having PCC scores higher than 0.9 in MAM, all in JJA, 4 in SON and 24 in DJF. The CMIP5 models simulate temperature better than precipitation, but substantial spatial heterogeneity exists and many models show limited skills in simulating precipitation (Aloysius et al., 2016; Vizy and Cook, 2012). Furthermore, the performance of MMM is examined in reproducing the distribution of temperature and precipitation. The MMM has PCC of 0.91 for MAM, 0.95 for JJA, 0.94 for SON and 0.95 for DJF for precipitation, while for surface air temperatures, the respective values are 0.96 for MAM, 0.98 for JJA, 0.83 for SON and 0.96 for DJF. For temperature, the individual models that perform best are MIROC4h (for MAM and DJF), MPI-ESM-LR and CSIRO-MK3.6.0 (for JJA), CSIRO-MK3.6.0 (for SON) while the worst performance is shown by INM-CM4 for all seasons.

The performance of individual models as well as MMM is also examined for four sub-regions of Africa, that is, North Africa (10°–30°N; 20°W–30°E), West Africa (11.5°S–15°N; 20°W–25°E), East Africa (11.5°S–15°N; 25°E–52°E) and South Africa (35°S–11.5°S; 10°W–52°E) (as shown in Figures S1 and S2). Over the North Africa, for precipitation (as shown in Table S1), MPI-ESM-LR have shown the best performance during MAM, DJF and SON while GISS-E2H shows the best performance during DAG, MAM and DJF and GFDL-ESM2M during DJF and SON, MIROC5 for DJF. For temperatures (as shown in Table S6), models that show the best performance are MIROC5 for MAM and DJF, GFDL-CM3 during JJA, MPI-ESM-LR during SON while models with the worst performance are IPSL-CM5-LR during MAM, EC-EARTH during JJA and INM-CM4 for SON and DJF. Over West Africa, for precipitation (as shown in Table S2), models with the best performance are GFDL-CM3 (MAM), MPI-ESM-LR (JJA), GFDL-CM3 (SON) and CESM-CAM during DJF. Models with worst performance are CSIRO-MK3.6.0 for MAM, and MIROC5 for JJA, SON and DJF. For temperatures (as shown in Table S7), MPI-ESM-LR (MAM), IPSL-CM5-LR (JJA), HadCM3 (SON)
and CSIRO-MK3.6.0 (DJF) models show high performance while EC-EARTH (MAM, JJA and SON) and INM-CM4 (DJF) models show the worst performance. Over East Africa, for precipitation (as shown in Table S3), the best performance is shown by INM-CM4 for MAM, HadGEM2-ES for JJA, EC-EARTH for SON and EC-EARTH for DJF.
FIGURE 5  Pattern correlation coefficient (PCC) vs the normalized root mean square error (RMSE) of each of the CMIP5 models as well as that of the multimodel mean for precipitation (1st column) and surface air temperature (2nd column) for the four seasons with respect to CRU data for MAM, JJA, SON, and DJF
while the worst performance was shown by MIROC5 (MAM, JJA and SON), MIROC4h (DJF). The temperature (as shown in Table S8) investigations have shown that MIROC4h (during MAM, JJA and DJF) and MPI-ESM-LR (during SON) show a good performance while INM-CM4 shows the worst performance during all seasons. Over South Africa, for precipitation (as shown in Table S4), CSIRO-MK3.6.0 (MAM), MIROC4h (JJA), IPSL-CM5-MR (SON), and FGOALS-g2 (DJF) show good performance while NorESM1-M (MAM, SON and DJF) and INM-CM4 (JJA) showed the worst performance. For temperature (as shown in Table S9), MIROC5 exhibit the best performance during all seasons while, worst performance are shown by INM-CM4 (during MAM, JJA, and SON), EC-EARTH (during DJF).

4 | CONCLUSIONS

This paper assesses the performance of 28 CMIP5 MMM in simulating seasonal mean precipitation and surface temperature over Africa. The MMM of 28 CMIP5 models for the 31-year period (1975–2005) are compared with CRU observations. Model performance is evaluated in view of the PCC and RMSE. The MMMs captures the geographical distribution of precipitation and temperature for all four seasons. The PCC between observed and MMM precipitation exceeds 0.95 for JJA and SON seasons. Similarly, the MMM captures the distribution of temperature with PCC values exceeding 0.95 for three seasons, excluding SON. The MMM overestimates the precipitation for MAM, SON, and DJF seasons. The overestimation of MMM precipitation over the Gulf of Guinea and Eastern Africa might be due to the lateral boundary condition errors in the CMIP5 models (Dike et al., 2015) and the presence of mountain ranges. The latitudinal shift in the precipitation and temperature maxima with the location of the ITCZ is also apparent in the MMM. The MMM can depict the present seasonal climatological precipitation and temperature patterns over Africa, however, the trends are not properly captured by the MMM. The best and worst performing individual model over the whole Africa and its four sub-regions (South, North, East, and West) are also presented in this study. It can therefore be concluded that CMIP5 MMM offers good reliability for the climatological mean features over Africa but the failure in its ability to capture the historical trends makes its usage to envision the future climate change questionable.

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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