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Evaluation of CMIP6 model skills in simulating tropical climate extremes over Malawi, Southern Africa

Bernard Mmame[1] · Cosmo Ngongondo[2]

Abstract

Malawi, a developing country in southeast Africa, is one of the most vulnerable countries to climate change and associated impacts. Availability of observed data to inform our knowledge on climate change is however, a key challenge and has led to relatively little research in the subject. Alternative climate data products, such as the Global Climate Models (GCMs) phase6 of Coupled Model Intercomparison Project (CMIP6), accords the chance to bridge this knowledge gap. These products however, need some validation against observed data to ascertain their level of performance. This study therefore, evaluates the ability of nineteen CMIP6 models in simulating both annual and seasonal temperature and precipitation over Malawi from 1980 to 2014. Observed Model performance metrics such as bias, root mean square error (RMSE), spatial correlation coefficient, standard deviation and Percentage Bias (PBIAS) were employed to assess the ability of the individual models. Our quantitative analysis shows that most of the models could simulate both temperature and precipitation over the study area, with correlation coefficient values of over 0.70, RMSE values between 0.9 and 2.0 and PBIAS of ≤ 10%. The results are suggesting better performance of CMIP6 than those reported in previous studies over the study domain using CMIP3 and CMIP5 model datasets. Of all the nineteen models evaluated in this study, no single model performed best compared to observed dataset, because the models are varying in performance from season to season. Hence, climate end users are advised to use simulations of temperature and precipitation over the study area from CMIP6 models with care for decision making on the mitigation and adaptation of climate change.

Keywords Temperature · Precipitation · CMIP6 · Climate change · Bias · Malawi

Introduction

Previous studies have revealed that extreme climate events have huge negative impact on the economy and livelihoods of people (Niang et al. 2014). Therefore, it is of great importance to understand the spatial distribution and intensity of these events so that losses which are associated with the events can be reduced. However, observed climate data to support such understanding is very scarce especially in many developing regions (Seyama et al. 2019). Consequently,

studies have used alternative climate data products from models and satellites to bridge the knowledge gap. For example, studies done by Dunning et al. (2017), Rowell (2019) and Wainwright et al. (2019) utilised global models' datasets to have an understanding of the past and future changes in climate change at global and regional levels. Koutroulis et al. (2016), Kumar et al. (2013, 2014), Sillmann et al. (2013) and Nguyen et al. (2017) used Version 5 of experiments from Coupled Model Intercomparison Project (CMIP5) to show that the models were able to mimic precipitation at global level. Wainwright et al. (2019) and Rowell (2019) also used CMIP5 datasets to prove that the models had the ability to reproduce precipitation at regional level. Libanda and Nkolola (2019), used CMIP5 datasets to show that the models were somehow able to reproduce precipitation over Malawi. Regional evaluation of models has shown that GCMs are to some extent good when it comes to simulating temperature trends, but they tend to overestimate precipitation in all seasons for Southern Africa (Flato et al. 2014; Buontempo et al.

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2015). Dong and Dong (2021) found that CMIP6 models were be able to better simulate the interannual variability of extreme precipitation events in the Asian region. Taylor et al. (2023) in their study reported that CMIP6 models were broadly capable of mimicking temperature and precipitation over Pacific Northwest. Kim et al. (2014) have also reported that climate projections using GCMs represent changes over a large area, however, to conduct a context-specific impact and adaptation assessments, a more detailed local understanding is needed. The multi-model ensemble mean (MME) and median of these models have proved to reproduce precipitation much better than individual models (Mehran et al. 2014; Samuels et al. 2018; Sillmann et al. 2013; Sonkoué et al. 2019). Kalognomou et al. (2013) and Endris et al. (2013) also reported that an ensemble mean of ten models was able to simulte precipitation over southern and eastern Africa respectively.

Previous studies have shown that CMIP5 have the ability to mimic precipitation and temperature but, the challenge of spatial biases in the models is not fully solved (Sillmann et al. 2013; Yang et al. 2015; Zebaze et al. 2019). A study done by Taylor et al. (2012) revealed that the coarse horizontal resolutions also contribute to the biases in the models. Even though naturally, Regional Climate Models (RCMs) inherit the biases of the GCMs which form their boundary conditions, but Buontempo et al. (2015) in their studies revealed that local climate forcings and the RCM formulation have a greater influence over the results and decrease the impact of these biases over African region. Kharin et al. (2013) reported that the there are some uncertainties in CMIP6 models which need to be addressed especially, over the tropical and subtropical regions. The GCM models that have contributed to the latest version of CMIP6 consist of new physical processes and high resolution compared to previous versions like CMIP5 and CMIP3 (Eyring et al. 2016). This therefore, is a clear indication that CMIP6 models have improved in as far as simulations of precipitation are concerned compared to previous versions (Dunning et al. 2017). Akinsanola et al. (2020), Gusain et al. (2020) and Ha et al. (2020), have reported that the current state-of-art climate models are far much better than previous version of CMIP ensembles. This shows that there are effective improvements in the models in simulating large-scale patterns of climate variables. Even though the models are reported to be able to reproduce precipitation and temperature, but some models are overestimating or underestimating the two parameters over some regions globally. Therefore, it is significant to critically examine the skills of CMIP6 models in simulating temperature and precipitation over Malawi in order to find out if, the new models (CMIP6) have improved in capturing the physics controlling temperature and precipitation over the study domain. Gou et al. (2019) in their study reported that, the widespread temperature increases have great negative impacts on the hydrological cycle. The better performance of models in simulating the relationship between precipitation and temperature is very vital in increasing their ability to predict well the effects of climate systems such as El Niño-Southern Oscillation (McKenna et al. 2020; Zhou et al. 2020; Beobide-Arsuaga et al. 2021; Yang and Huang 2022) and decrease the model bias in temperature pattern (Ying et al. 2022). The main aim of this study is to examine the ability of CMIP6 models in reproducing temperature and precipitation over Malawi (a country in southeast Africa) from 1980 to 2014.

Data and methodology

The present study has used historical simulations of nineteen CMIP6 models to understand their ability to simulate temperature and precipitation by evaluating them against observation dataset. The study has utilised r1i1p1f1 members of the models as shown in Table 1. Our choice of models for climatological evaluation has depended on the choice of observation dataset as reported by Sillmann et al. (2013). The temperature and precipitation model datasets were assessed against observation datasets from Malawi Department of Climate Change and Meteorological Services (MDCCMS). The names and location of the stations where the datasets were taken are shown in Fig. 1. These datasets have proven to be reliable for evaluating climate models as reported by Libanda and Nkolola (2019).

In this study, all the datasets were re-gridded to a 2.5° × 2.5° resolution by using a technique called "bilinear interpolation" method. This was done with the idea of having datasets of common resolution because the model datasets are of varying resolutions as indicated in Table 1. Mmame et al. (2023b) revealed that bilinear interpolation is just a basic re-gridding method. Libanda and Nkolola (2019) and Ongoma et al. (2019) reported that bilinear interpolation technique counterbalances the differences in resolution when conducting comparative analyses.

The study has also assessed the ability of each model in simulating temperature and precipitation by calculating biases (Yazdandoost et al. 2021) using the following equation:

$$B = M - O \tag{1}$$

where B is the bias being calculated, M is the model datasets and O is the observed dataset. Take note that, one can calculate bias if the two datasets are of the same resolution and length.

The comparison of each grid point of the models and observation were assessed by calculating the statistical metrics. This was done with the idea of checking the

Table 1 Showing a list of CMIP6 models used in this study

S/N	Model name	Modellig group	Country	Resolution (Lat × Lon)	Members
1	ACCESS-CM2	CSIRO-ARCSS	Australia	192 × 144	r1i1p1f1
2	ACCESS-ESM1-5	CSIRO	Australia	192 × 145	r1i1p1f1
3	CanESM5	National Center for Atmospheric Research	Canada	128 × 64	r1i1p1f1
4	CESM2	National Center for Atmospheric Research	USA	288 × 192	r1i1p1f1
5	CESM2-FV	National Center for Atmospheric Research	USA	144 × 96	r1i1p1f1
6	CESM2-WACCM	National Center for Atmospheric Research	USA	288 × 192	r1i1p1f1
7	CESM2-WACCM-FV2	National Center for Atmospheric Research	USA	144 × 96	r1i1p1f1
8	FIO-ESM-2-0	The First Institute of Oceanograpy	China	192 × 288	r1i1p1f1
9	INM-CM4-8	Institute of Numerical Mathematics	Russia	180 × 120	r1i1p1f1
10	INM-CM5-0	Institute of Numerical Mathematics	Russia	180 × 190	r1i1p1f1
11	IPSL-CM6A-LR	Institute of Pierre-Simon Laplace	france	144 × 143	r1i1p1f1
12	MCM-UA-1-0	Manabe Climate Model	USA	96 × 80	r1i1p1f1
13	MIROC6	AORI-NIES-JAMSTER	Japan	256 × 128	r1i1p1f1
14	MPI-ESM1-2-HAM	Max Plank Institute for Meteorology	Germany	192 × 96	r1i1p1f1
15	MPI-ESM1-2-LR	Max Plank Institute for Meteorology	Germany	192 × 96	r1i1p1f1
16	MRI-ESM2-0	Meteorological Research Institute	Japan	360 × 320	r1i1p1f1
17	NESM3	NUIST ESM	China	192 × 96	r1i1p1f1
18	NorCMPM1	The Norwegian Climate Prediction	Norway	96 × 144	r1i1p1f1
19	NorESM2-LM	Norwegian Climate Centre	Norway	144 × 96	r1i1p1f1

spatial ability of the models in reproducing temperature and precipitation. The statistical metrics used in this study are Root-mean-square error (RMSE), correlation coefficient (CC) and standard deviation (SD). RMSE is mathematically defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{obs_i} - x_{model_i})^2}{n}} \qquad (2)$$

where x_{obs_i} denotes the observation data and x_{model_i} refers to the modelled data at time or place *i* as reported by Brigadier et al. (2016).

The study has also used Pearson correlation coefficient. This is nothing but, a value that is obtained after dividing the covariance of two variables by the product of their standard deviation (Brigadier et al. 2016). The mathematical definition of correlation coefficient is:

$$CC = \frac{\sum_{i=1}^{n}(x_i - \bar{x}_i)(y_i - \bar{y}_i)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y}_i)^2}} \qquad (3)$$

where *CC* represents the calculated correlation coefficient value, x is the observed dataset and y is the modelled dataset. The values of correlation coefficient are between − 1 to 1. In this case, 1 shows that there is a strong relationship and − 1 represents weak relationship between two parameters.

But, zero indicates no relationship between the two parameters under study.

These statistical metrics have been presented in Taylor diagrams (Taylor 2001) (annually and seasonally). Taylor diagram integrates a number of evaluation metrics for presentation at the same time, showing accuracy of the model matching of the observed data in terms of standard deviation, correlation coefficient as well as root mean square error (Taylor 2001). The central point to Taylor diagram is that the correlation coefficient, standard deviation and central RMSE of the observed and simulated data should satisfy (Taylor 2001; Yan et al. 2022) the following equation:

$$RMSE^2 = \sigma_{obs}^2 + \sigma_{model}^2 - 2\sigma_{obs}CC \qquad (4)$$

where σ_{obs} is the standard deviation of the observed data which is mathematically defined as:

$$\sigma_{obs} = \sqrt{\frac{\sum_{n=1}^{n}(x_{obs} - \bar{x}_{obs})^2}{n}} \qquad (5)$$

and σ_{model} is the standard deviation of the simualted datasets which is mathematically defined as:

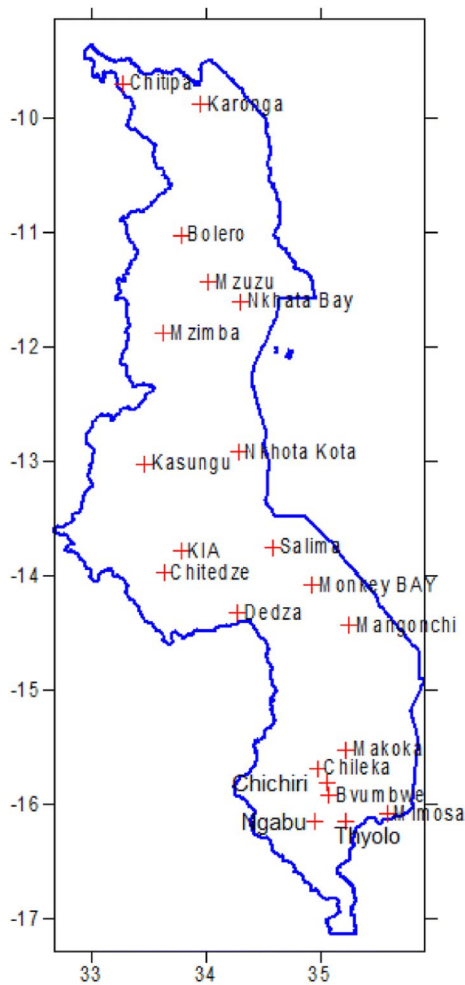$$\sigma_{model} = \sqrt{\frac{\sum_{n=1}^{n}(x_n - \bar{x})^2}{n}} \qquad (6)$$

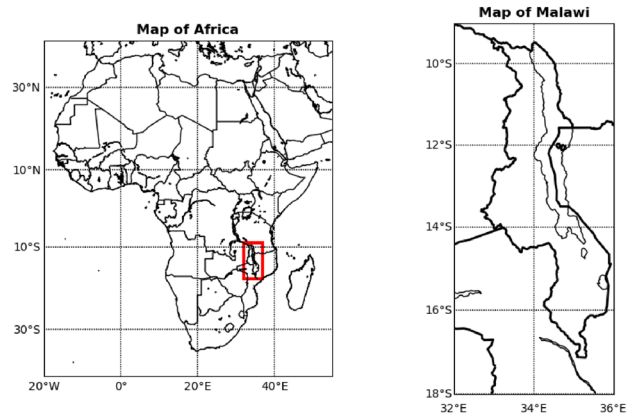Fig. 1 Names and location of stations used in the present study

Fig. 2 Map of Africa (left panel) with red rectangle showing the geographical location of Malawi. The right panel shows the extracted area of interest (Map of Malawi) from map of Africa

Study area description

Malawi (Fig. 2) is a southeast African country located between latitudes 9° and 18°, and longitudes 32° and 36°. It is surrounded by Tanzania to the north, Zambia to the west and Mozambique to the south. The topographical features vary from place to palce due to the Great Rift Valley that passes from the north to the south of the country. Mcsweeney et al. (2010) reported that, a lot of Malawi's land mass lies between 800 and 1200 m with highest peaks of up to 3000 m around Mulanje mountain area. Reason (2017) in their study revealed that, a number of high-elevation areas in the country of Malawi experience relatively cool temperatures. But generally, temperatures vary from 18 to 19 °C in winter months over Malawi. According to Mcsweeney et al. (2010), the warmest months in this country are September through January when the country experiences temperatures of 22–27 °C. Ngongondo et al. (2015) also reported the same range of temperature in their study over the study domain. Malawi's rainfall vary in space and time due to topographical variations which cause localised precipitation activities around high-altitude regions (Mcsweeney et al. 2010). Apart from topography, other processes that generate rainfall over the country are influenced by the north–south movement of the ITCZ, its position and even the strength of the ITCZ (Nicholson and Dezfuli 2013). Mmame et al. (2023a) have also reported in their study that, seasonal fluctuations in east African rainfall (where Malawi is located) are influenced by the movement of the northern hemisphere midlatitude circulation and the El Nino Southern Oscillation (ENSO).

where $\bar{x}_{obs}$ and $\bar{x}$ is the mean of the observed data and model data respectively.

For identification of the best models, PBIAS technique was employed (Gupta et al. 1999; Libanda and Nkolola 2019). Overall, PBIAS gives either positive or negative values of the model datasets from observed datasets. The values of PBIAS are presented in percentage where, low percentage denotes that the model is simulating accurately. The models are said to be overestimating if the PBIAS values are positive but negative values reveal that the models are underestimating in relation to observed dataset. The mathematical definition of PBIAS is:

$$PBIAS = \frac{\sum_{i=1}^{n}(H_i - J_i)}{\sum_{i=1}^{n} J_i} \times \% \tag{7}$$

where PBIAS denotes the deviation of the data being evaluated presented in %. H_i represents modelled dataset and J_i denotes observed dataset.

Results and discussion

Observed and simulated precipitation over Malawi—South East Africa

Figure 3 shows mean annual cycle of precipitation from CMIP6 models and observational (rain gauge) datasets. From this figure, it is clear that, all the models reported in this study are able to mimic rainfall over the study domain. The models are able to capture the dry period which starts in May to around end October (Jury and Gwazantini 2002; Kumbuyo et al. 2014; Libanda and Nkolola 2019). More rains are reported from December to around March. Results from this study are in agreement with previous studies reported by Kazembe (2014), Ngongondo et al. (2014), Libanda et al. (2017), and Libanda and Nkolola (2019). The ensemble mean is as well performing good in relation to the observed dataset (rain gauge). It should be noted that, temporal plots have limitation in as far as model evaluation is concerned because it is difficult to critically analyse the characteristics of each model when the variation of the models are very close to each other (Taylor 2001). In the present study, the characteristics of models have been critically analysed and presented in Taylor diagrams (annually and seasonally).

Figure 4 shows annual spatial distribution of rainfall over Malawi. From this figure, it is evident that, observational dataset (rain gauge) is able to mimic the characteristics of the ITCZ (Brigadier et al. 2015) whereby, the northern region of the country experiences a bit more rainfall at the beginning of the rain season thus, around November/December than the southern region (Brigadier et al. 2015). This is a clear indication that the ITCZ has arrived in the country from the northern region (Reason 2017). It is interesting to observe that, as the ITCZ moves towards the southern region of the study area, there is

precipitation deficiency in the northern region of the country. Ngongondo et al. (2011) and Libanda et al. (2017) also reported similar characteristics in their studies.

Studies done by Otieno and Anyah (2013) and Mumo and Yu (2020) have revealed that CMIP models have challenges in showing wet or dry biases during NDJF or MAM rainy seasons over some parts of east African countries like Malawi. Funk et al. (2008), Lyon and DeWitt (2012) and Liebmann et al. (2014) in their studies reported that, the dry biases over east African contries like Malawi are due to decrease in precipitation. Figure 5 shows precipitation bias over the study domain. It is observed that some models such as MPI-ESM1-2-LR and MCM-UA-1-0 are showing clear wet bias over the study domain. This means that, these models overestimated precipitation over the area compared to observed datasets for the study period.

Libanda and Nkolola (2019) reported that some studies on the performance of CMIP models were showing somehow weak correlation coefficients between modelled datasets and observed (rain gauge) precipitation datasets over some east African countries such as Malawi. The studies have further revealed that the weak correlation between observed dataset and CMIP6 model datasets may be associated with the type of observation datasets used in a study. For example, in Argentina, Pinto et al. (2018) reported low RMSE values between models and observation due to the type of observed datasets they employed in their study. Figure 6 shows the Taylor diagram for annual and seasonal precipitation over Malawi between observed data (rain gauge) and CMIP6 models from 1980 to 2014. Our quantitative analysis of the models for annual rainfall varies from model to model as shown in Fig. 6. Some models used in the present study have exceeded the 95% confidence level. This confidence level is an indication that the models are able to simulate the spatial variability of precipitation over Malawi. The annual SDs ranged from 1.20 to 1.85 and some models like IPSL-CM6A-LR,

Fig. 3 Time series of seasonal (1980–2014) mean precipitation (mm/day) distribution from CMIP6 models datasets and Observed dataset (Rain gauge)
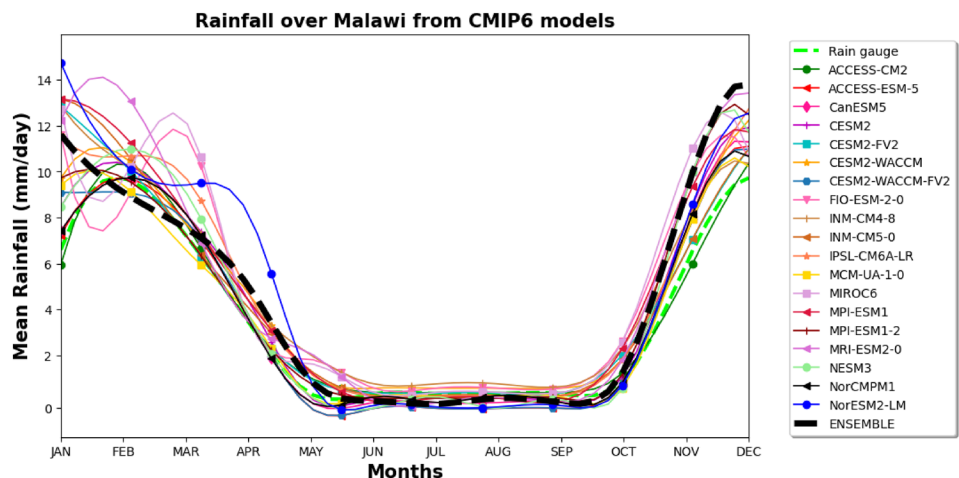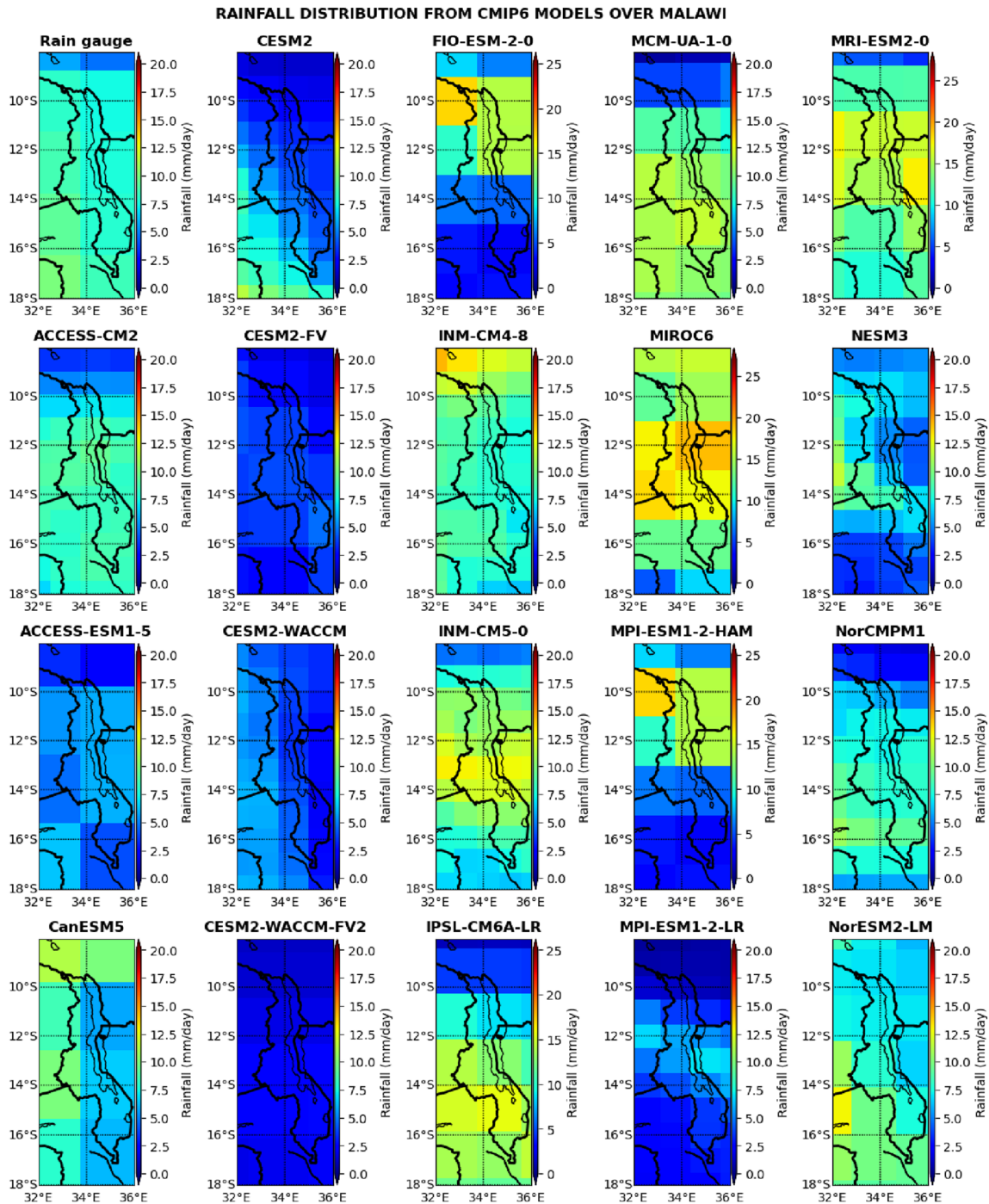
Fig. 4 Annual (1980–2014) mean precipitation (mm/day) distribution from nineteen CMIP6 models and Observation (Rain gauge) over Malawi

CESM2-FV2 and NorESM2-LM are larger than 1.5, showing that they greatly overestimate the spatial annual precipitation variability over the study domain. The annual RMSE values are ranging between 1.2 and 2.0 for the entire study period. The correlation coefficient values are ranging from 0.15 to 0.65. The correlation coefficient (see Fig. 6) values found in this study are somehow high compared to those found by other researchers such as Libanda and Nkolola (2019) and Ongoma et al. (2019) over the same study domain. A statistical metrics summary of annual and seasonal ranges of the comparative analysis between observed (rain gauge) precipitation data and CMIP6 model data is presented in Table 2

RAINFALL BIAS OF NINETEEN CMIP6 MODELS
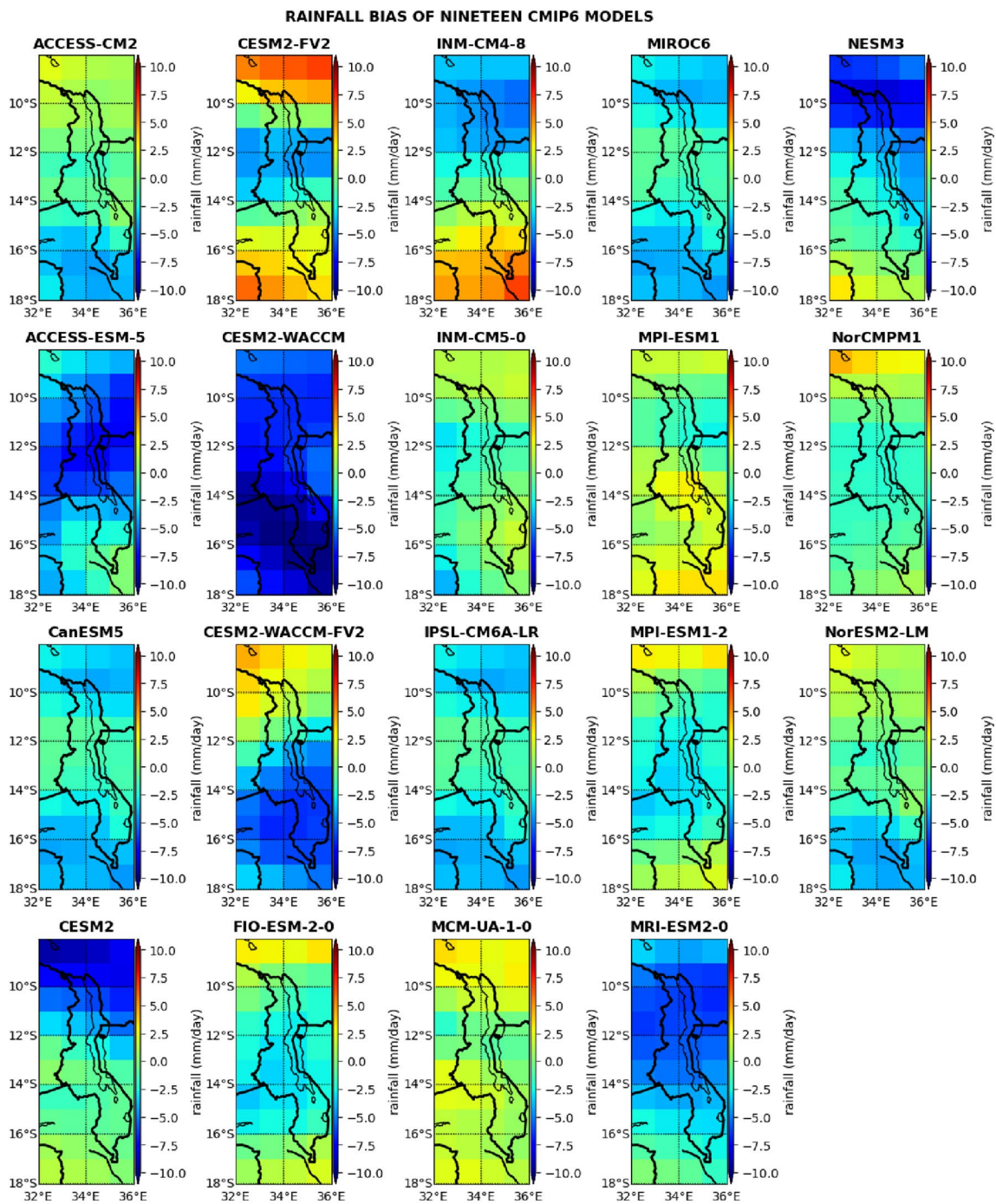
Fig. 5 Annual mean precipitation (mm/day) bias from CMIP6 models and observation (Rain gauge) from 1980 to 2014

Observed and simulated temperature over Malawi—South East Africa

Figure 7 shows seasonal time series variations of temperature from CMIP6 models over Malawi from 1980 to 2014. It is evident from this figure that, the models were able to sufficiently mimic the annual cycle of temperature over the study domain. Temperatures were ranging from 13.5 to ~ 31 °C. The models have been able to reproduce Malawi's two main seasons properly. The first one is called cool dry season which starts in May to somewhere around September having temperatures between ~ 13 °C and 17 °C. Hot wet season which starts from October through April with high temperatures of up to ~ 31 ° is the second season. These results are in agreement with those reported by Warnatzsch and Reay
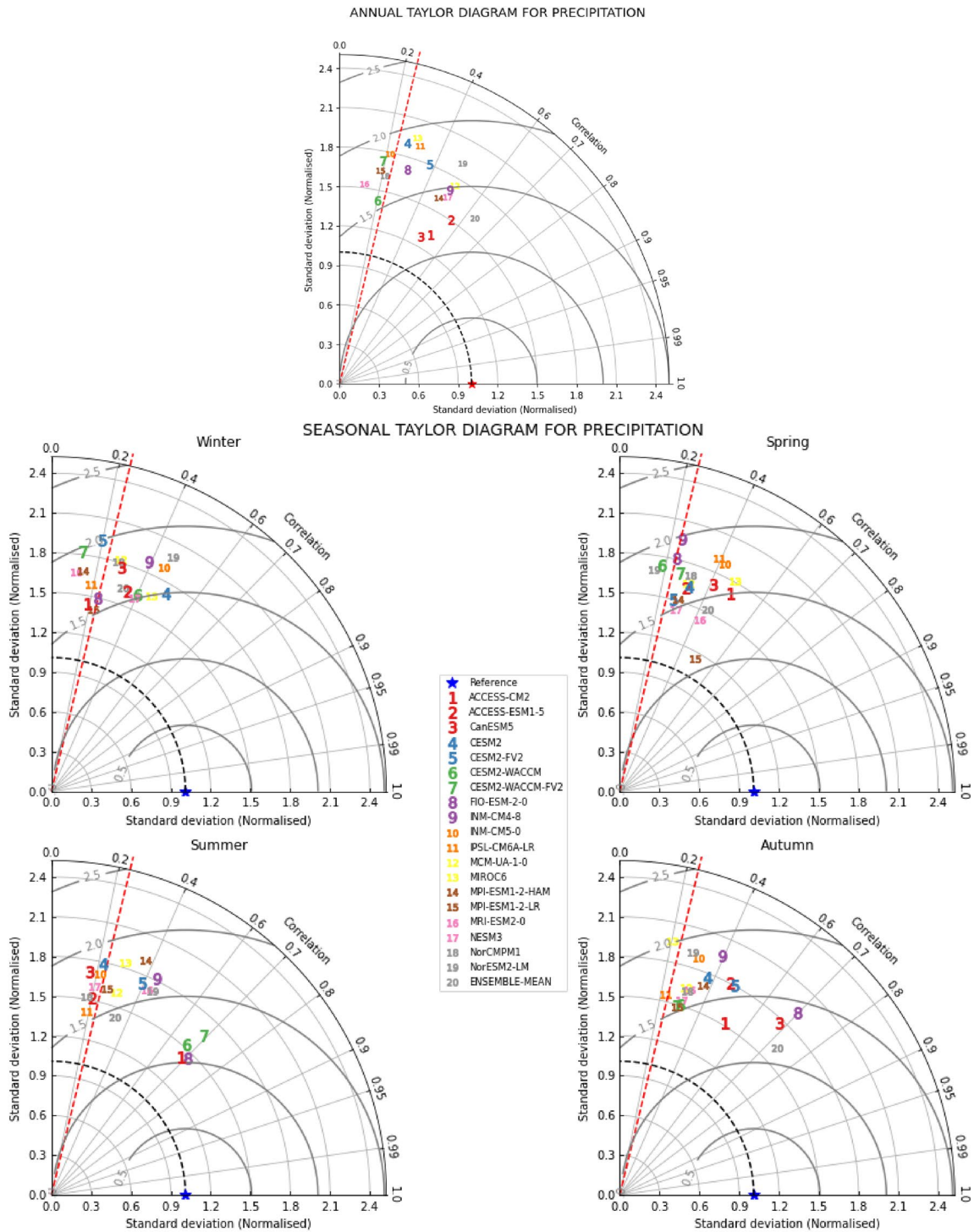
Fig. 6 Taylor diagram for annual and seasonal precipitation over Malawi (southeast African country) between observed dataset (Rain gauge) and CMIP6 model datasets from 1980 to 2014. The numbers on the Taylor diagram denote the models ID as shown on the legend and as listed in Table 1

Table 2 A statistical metrics summary of annual and seasonal ranges of the comparative analysis between observation (rain gauge) precipitation data and nineteen CMIP6 model data

Time/period	RMSE	CC	SD
Annual	1.20–2.00	0.15–0.65	1.20–1.85
Winter	1.40–2.00	0.16–0.46	1.40–1.87
Spring	1.10–2.00	0.18–0.56	1.11–1.88
Summer	1.00–1.80	0.19–0.71	1.30–1.90
Autumn	1.20–2.00	0.20–0.74	1.40–1.99

(2019). The ensemble mean of the models is also performing good in reproducing temperature over the study domain. A number of studies have reported that temperature is increasing in recent decades, for example, Warnatzsch and Reay (2019) showed that temperature is increasing over Malawi. This study has also found similar trends, with temperatures as high as 31 °C as it is shown in Fig. 7.

Spatially, temperature is to some extent consistent across the country as shown in Fig. 8. Though some models are indicating a bit low temperature (1–2 °C difference) in relation to other models and even observation dataset. Unlike Warnatzsch and Reay (2019) who reported higher temperatures over the southern region, this study indicates that temperature is more or less the same over both southern and northern region of the study domain.

Figure 9 shows annual temperature bias from CMIP6 models and observation. It is evident from this plot that, some models such as MIROC6, CanESM5, IPSL-CM6A-LR and MRI-ESM2-0 are indicating cool bias over the study domain. This means that these models were underestimating temperature over the study area. On the other hand, some models like CESM2-FV2, NorCMPM1, MPI-ESM1-2, MCM-UA-1-0 and FIO-ESM-2-0 are exhibiting warm bias. This is an indication that some CMIP6 models are overestimating temperature over Malawi. Just as observed by

Warnatzsch and Reay (2019), the models are able to mimic both minimum and maximum temperatures over the study domain. High biases have been observed in high terrain and along lake Malawi. Timing as well as intensity changes in temperature have negative impacts on evapotranspiration.

Figure 10 is a Taylor diagram (Taylor 2001) which contains the information about root-mean-square error (RMSE), correlation coefficient (CC) and standard deviation (SD) between temperature from observation dataset and simulations from CMIP6 models. As shown in Fig. 10, the CCs of the nineteen models between the simulated and observed annual temperature are varying between 0.40 and 0.79. This shows that the observational temperature distribution over Malawi is reproduced very well by the models because the CC values are somehow high. The SD values are ranging from 1.20 to 1.90 and the RMSE values are between 0.90 and 1.75. This clearly indicates that, the models are reasonably able to depict the spatial variability of annual temperature over our study domain, Malawi. The values of RMSE found in this study are in agreement with the findings of Sheffield et al. (2013) who also found good values of RMSE across Africa as compared to other regions of the world.

The seasonal quantitative analysis shows that, the CC values between CMIP6 models and observed temperature is ranging between 0.39 and 0.71 in winter season. The SD values are varying between 1.30 and 1.90 while the RMSE values are ranging from 1.20 to 1.80. This is an indication that the models are reasonably mimicking the spatial mean winter temperature over Malawi. Similarly, spring season also shows that the models are able to simulate temperature over Malawi since the CC values of the models are found between 0.40 to 0.70 which are strong correlation coefficient values as it is shown in Fig. 10. The SD values between modelled datasets and observed data are varying between 1.10 and 2.00 and RMSE values are found between 0.80 and 1.81. A statistical metrics summary of annual and seasonal ranges of the comparative analysis between observed

Fig. 7 Time series of seasonal mean temperature from nineteen CMIP6 models and Observed dataset from 1980 to 2014
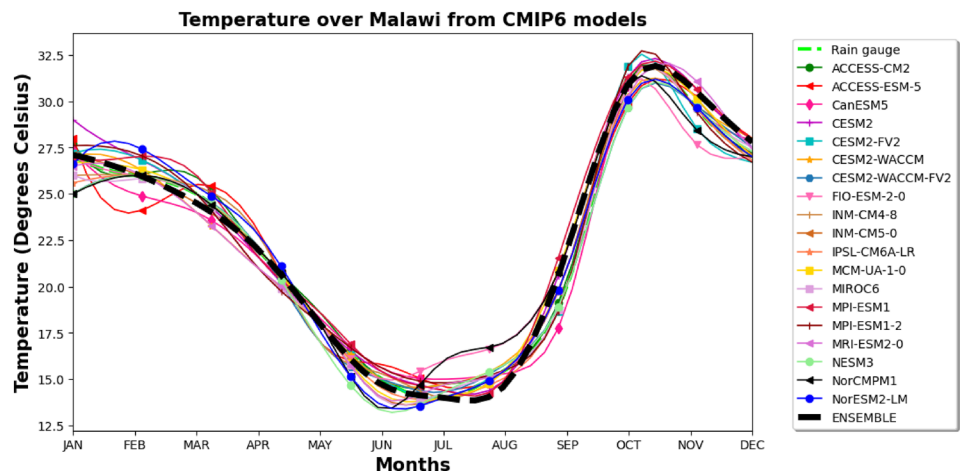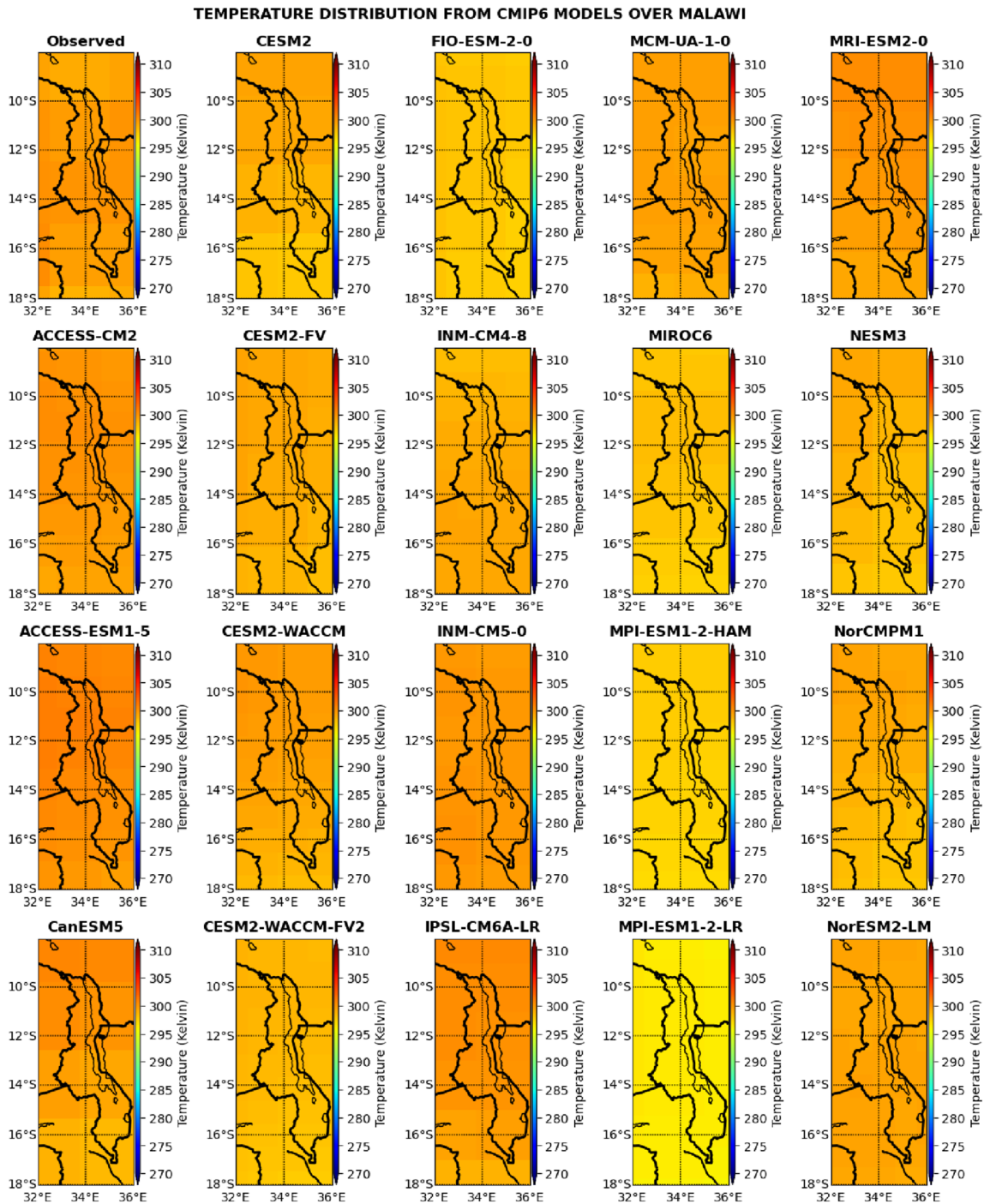
Fig. 8 Annual (1980–2014) mean temperature (K) distribution from nineteen CMIP6 models and Observation over Malawi

temperature dataset and simulated CMIP6 model dataset has been shown in Table 3

For identification of best performing models, PBIAS technique was applied between simulated and observed
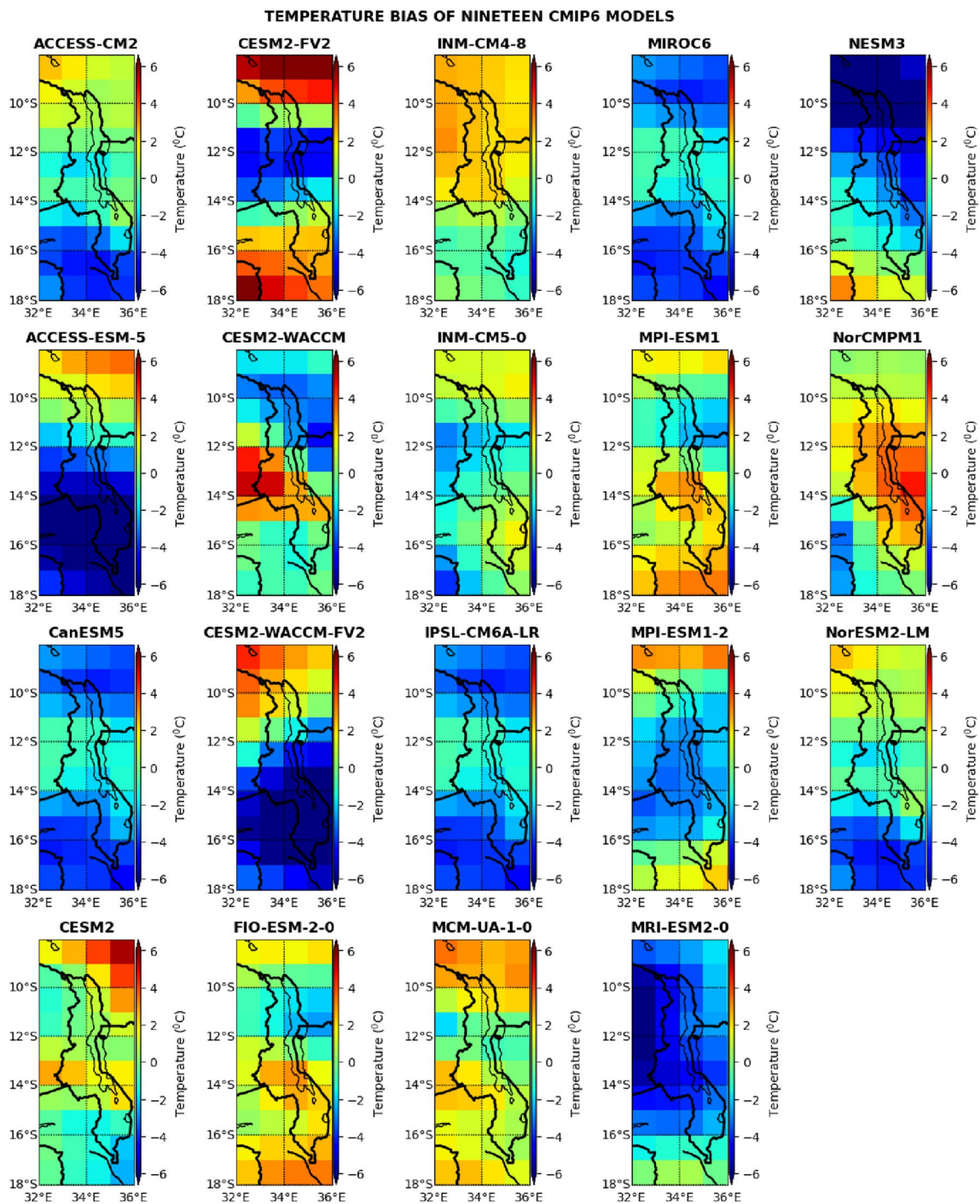
Fig. 9 Annual mean temperature (°C) bias from CMIP6 models and observation for period from 1980 to 2014

datasets. Our analysis is showing that, all the models are performing good in simulating precipitation over Malawi because they have low PBIAS values of $(\pm) \leq 10\%$ (Libanda and Nkolola 2019) as shown in Table 4. The same is the case with temperature, all models are performing good since they have PBIAS of $(\pm) \leq 10\%$ as indicated in Table 4.

Conclusion

The main aim of this study was to examine the performance of individual CMIP6 models in simulating temperature and precipitation over Malawi, a country which is found to the southeastern part of Africa. Our quantitative results have
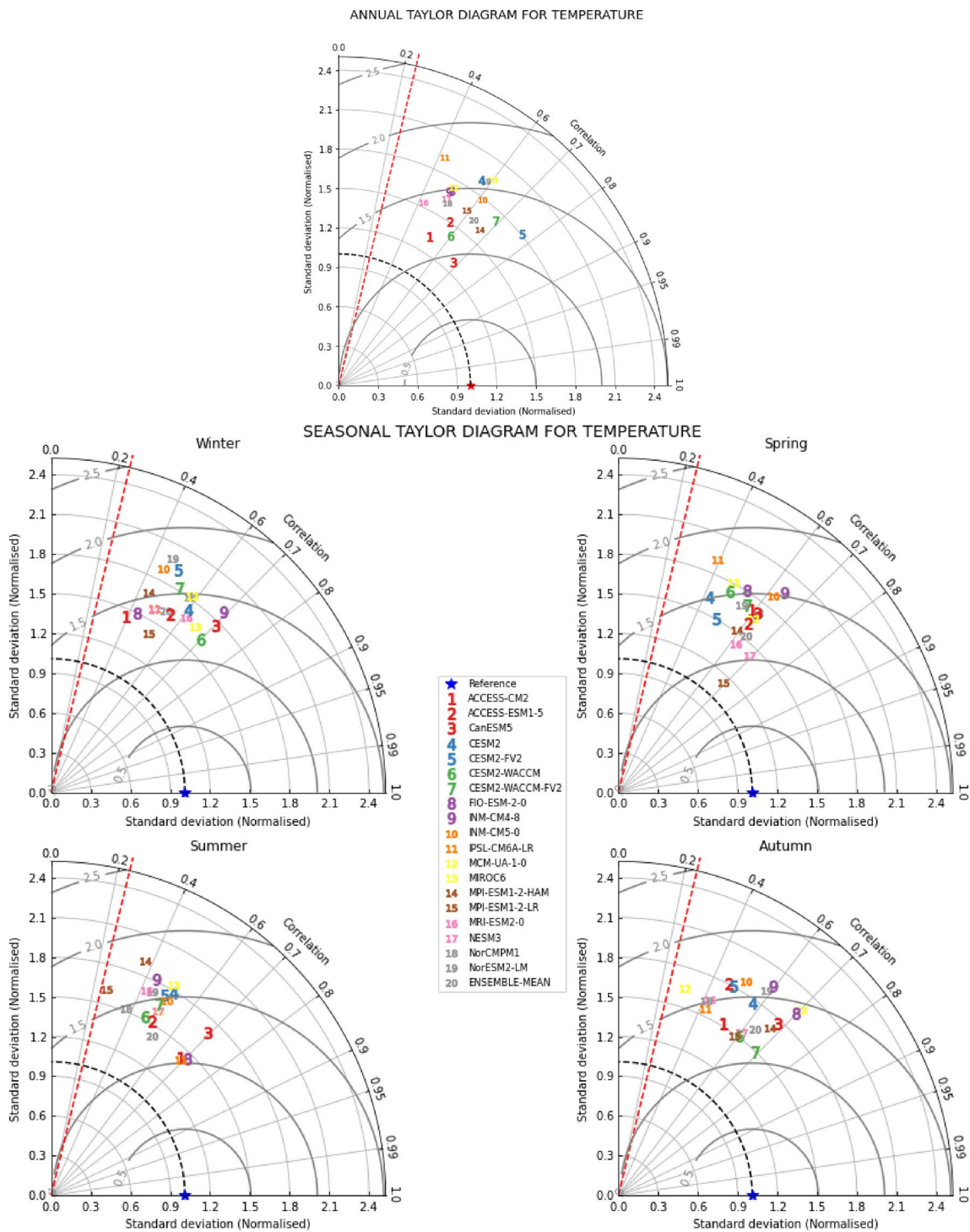
Fig. 10 Taylor diagram for annual and seasonal precipitation over Malawi (southeast African country) between observed dataset and CMIP6 model datasets from 1980 to 2014. The numbers on the Taylor diagram denote the models ID as shown on the legend and as listed in Table 1

shown that, the models analysed in this study have improved in reproducing temperature and precipitation over the study domain. The present study has reported correlation coefficient values which are somehow higher than those found

Table 3 A statistical metrics summary of annual and seasonal metrics ranges of the comparative analysis between observation temperature data and nineteen CMIP6 model data

Time/period	RMSE	CC	SD
Annual	0.90–1.75	0.40–0.79	1.20–1.90
Winter	1.20–1.80	0.39–0.71	1.30–1.90
Spring	0.80–1.81	0.40–0.70	1.10–2.00
Summer	1.00–1.80	0.21–0.71	1.40–1.90
Autumn	1.10–1.66	0.30–0.70	1.50–2.00

in previous studies using previous versions of CMIP i.e. CMIP3 and CMIP5 datasets. The high correlation coefficient values indicate that, the models have greatly improved in simulating temperature and precipitation over the study domain. The study has also found that all the nineteen models evaluated are able to simulate temperature charachteristics over the entire country of Malawi i.e, the models are able to capture maximum and minimum temperatures over the study domain. After applying PBIAS technique, all the models are falling within the required range i.e. PBIAS values are found to be within $(\pm) \leq 10\%$

The models are also able to capture the spatial characteristics of precipitation over Malawi both annually and

seasonally. The models are capable of capturing both dry (May through September) and wet (December through April) seasons. Some of the models have been found to be overestimating precipitation over the study domain just like other studies have also previously reported. This means that, the problem of bias in these models has not been fully resolved. For precipitation, all models are as well performing good thus, they have PBIAS values within $(\pm) \leq 10\%$.

The models have shown a great ability in simulating both precipitation and temperature over Malawi. There are variations in the performance of the models from season to season. In general, there are some improvements in the performance of CMIP6 in simulating temperature and precipitation in comparison with previous versions of CMIP (i.e. CMIP3 and CMIP5) over the study domain. Even though the models are able to simulate the two parameters over the study domain, the deficiencies of the models have been extensively discussed under results and discussion section. It should also be noted that no single model in this study, has performed best in relation to observed dataset. Therefore, climate end users are strongly advised to use projections of temperature and precipitation over the study area from these CMIP6 models with care for decision making on the mitigation and even adaptation of climate change.

Table 4 Showing statistical summary of the comparative analysis between rainfall/temperature observation datasets and CMIP6 annual rainfall/temperature simulation datasets over Malawi

Model name	Mean precipitation (mm/day)	Mean temperature	Precipitation PBias (%)	Temperature PBias (%)
ACCESS-CM2	6.8	26.5	0.6	− 3.4
ACCESS-ESM1-5	6.7	27.1	2.1	− 5.5
CanESM5	7.0	26.0	− 2.3	− 1.5
CESM2	6.8	25.2	0.6	− 1.6
CESM2-FV	6.6	26.2	3.6	− 2.3
CESM2-WACCM	6.5	26.1	5.2	− 1.9
CESM2-WACCM-FV2	6.4	25.3	6.9	1.2
FIO-ESM-2-0	7.0	25.1	− 2.3	2.0
INM-CM4-8	7.2	25.0	− 5.0	2.4
INM-CM5-0	7.1	26.1	− 3.7	− 1.9
IPSL-CM6A-LR	7.1	26.3	− 3.7	− 2.7
MCM-UA-1-0	7.2	26.0	− 5.0	− 1.5
MIROC6	7.3	27.2	− 6.3	− 5.9
MPI-ESM1-2-HAM	6.9	24.8	− 0.9	3.2
MPI-ESM1-2-LR	6.7	24.1	2.1	6.2
MRI-ESM2-0	7.4	23.9	− 7.7	7.1
NESM3	6.8	26.4	0.6	− 3.0
NorCMPM1	6.9	25.8	− 0.9	− 0.8
NorESM2-LM	6.9	25.7	− 0.9	− 0.4
Ensemble-Mean	6.91	26.1	− 1.0	− 1.9
Observation	6.84	25.6	0	0

Declarations

Conflict of interest The authors declare no conflict of interest.

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