Evaluation of Extreme Drought and Flood Events in East Africa Based on CMIP Models

Zichen Miao*

College of Agricultural and Environmental Science, University of California, Davis, 95616, United States

*Corresponding author: zchmiao@ucdavis.edu

Abstract. This study evaluates 19 CMIP6 historical precipitation model datasets spanning 1979–2014, using the GPCP monthly and GPCC daily precipitation datasets as benchmarks to ensure comparability. The analysis compares individual model results against observational data to dissect simulation differences across various models. The evaluation covers several critical aspects of precipitation modeling, including climatological mean changes, which are examined through spatial distribution, range, and standard deviation. Seasonal changes are also scrutinized, focusing on the long rainy season (March–May) and the short rainy season (October–December) to capture seasonal precipitation dynamics. Furthermore, the study investigates interannual changes by analyzing precipitation trends and eigenvectors to understand long-term variability. Key findings include significant variability in model performance—INM-CM5-0 shows strong correlation with observations, while CNRM-CM6-1 performs poorly—and most models can basically simulate precipitation spatial patterns but with overestimation/underestimation in specific regions. Additionally, it assesses model performance in capturing extreme drought/flood events, providing insights for regional climate projection and disaster early warning.

Keywords: CMIP; Africa; drought; flood; climate.

1. Introduction

Drought and flood events in East Africa have long been a focus of international attention. Scholars have conducted extensive research on these disasters using various climate datasets and methodologies, achieving notable progress. For example, Bob et al. employed the Regional Climate Model (RegCM4) to study the atmospheric circulation mechanisms associated with extreme dry and wet events in East Africa, simulating the annual cycle, short rainy season mean rainfall, and interannual variability. However, their simulations exhibited deviations from observations, often underestimating rainfall [1]. Ongoma et al. investigated the variability of extreme rainfall events in East Africa using indices from the Expert Team on Climate Change Detection and Indices (ETCCDI). They found that arid and semi-arid regions experienced a significant reduction in annual total rainfall compared to other parts of East Africa, with an abrupt shift observed in the past decade, reflecting ongoing climate change [2]. Moses et al. examined the relationship between extreme rainfall events across different rainfall zones in East Africa and their connections with the El Niño-Southern Oscillation (ENSO) and the Indian Ocean Dipole Mode Index (DMI). Their study revealed that over half of the stations showed a declining trend in extreme heavy rainfall indices from 1960 to 2017, with low correlation coefficients between regions and considerable variability in extreme precipitation trends, warranting further investigation [3]. Mulugeta et al. analyzed tree-ring records to reconstruct precipitation patterns and concluded that the frequency of extreme drought events in the Upper Blue Nile Basin has been increasing [4]. Solomon et al. assessed trends and variations in temperature (1979–2010) and precipitation (1981–2016) extremes across East Africa, particularly in Ethiopia, Kenya, and Tanzania. They found that most observed temperature extremes after 2000 were higher than the long-term average, while precipitation indices exhibited both increasing and decreasing trends in Ethiopia, Kenya, and Tanzania, respectively [5]. Mary et al. quantified the nature, impacts, and large-scale climate drivers of extreme rainfall in Kenya during March and April 2018 [4]. Schmocker et al. calculated trends in mean precipitation and extreme indices for several rainy seasons in Kenyan highlands from 1979 to 2011, comparing them with reanalysis products. While

the reanalysis datasets aligned with observations regarding interannual variability, their correlation with monthly deviations (ratios) from the mean annual cycle was much weaker [6].

These studies demonstrate that meteorological research in recent decades has primarily focused on historical trends of extreme precipitation events in localized areas of East Africa. However, predicting the variability of extreme drought and flood events remains a challenge. The interactions between different climatic phenomena further complicate rainfall simulations, often introducing systematic errors. Most studies have concentrated on annual patterns of extreme precipitation, with limited exploration of seasonal details. Sub-seasonal assessments are rare, and quantitative research on the mechanisms driving drought and flood events during East Africa's long and short rainy seasons remains scarce. Updated and more comprehensive datasets are needed to deepen our understanding of these phenomena in the region.

2. Data and CMIP Models

This study utilizes the monthly precipitation data from the Global Precipitation Climatology Project (GPCP) (1979–2014), with a spatial resolution of 2.5° × 2.5° and units in mm/day (https://psl.noaa.gov/data/gridded/data.gpcp.html). For the simulation and analysis of extreme precipitation indices, the daily precipitation observation data employed are from the Global Precipitation Climatology Centre (GPCC) global land surface gridded daily precipitation dataset, with a resolution of 1° × 1° and units in mm/day, covering the period from January 1, 1988, to December 31, 2014 [7].

The model data used in this study consist of monthly precipitation datasets from 19 individual numerical models within Coupled Model Intercomparison Project Phase 6 (CMIP6), obtained from [8]. The model data utilize monthly precipitation outputs from historical simulations, covering the period from January 1979 to December 2014.

3. Climatological Mean Changes

3.1. Spatial Distribution

From the spatial distribution difference between model-simulated precipitation and observational precipitation, the observational data show that precipitation is relatively abundant in the western and southern parts of the study area, with the highest value in Uganda, reaching 5.34 mm/day; precipitation is relatively scarce in the eastern and northern parts, and a low-value center appears in the northeastern corner bordering Ethiopia, with the lowest value of 1.17 mm/day. Most models exhibit widespread overestimation of precipitation. Among them, MPI-ESM1-2-LR and INM-CM5-0 show overestimation in the entire region; models BCC-CSM2-MR and CNRM-CM6-1 show widespread underestimation of regional precipitation; most models simulate the overall precipitation distribution and pass the 90% confidence level. The correlation coefficients of models CMCC-CM2-HR4 and BCC-CSM2-MR both exceed 0.8, indicating a good simulation effect on the spatial distribution characteristics of observational results, and the correlation between INM-CM5-0 model data and observational data even reaches 0.9. CNRM-CM6-1 and CESM2-FV2 have the worst simulation effects (among which CNRM-CM6-1 is the worst, with a correlation coefficient of only 0.23); besides these two, the correlation levels of other models all exceed 0.6. In general, the models can basically simulate the spatial distribution characteristics of the precipitation climatological mean from 1979 to 2014, and only a few models have limited simulation capabilities.

A notable observation here is that while most models capture the general spatial pattern, the extreme differences between top-performing models (like INM-CM5-0 with 0.9 correlation) and underperforming ones (such as CNRM-CM6-1 with 0.23 correlation) highlight the significant variability in CMIP6 model performance for East African precipitation climatology.

3.2. Annual Precipitation Range

Observations show that the annual precipitation range of model data in the northwestern part of the study area is small, with weak precipitation variability, stable precipitation distribution, and low potential risk, while the range in the southeastern part is large, with significant precipitation changes. Overall, the precipitation range in the study area is relatively small, with the maximum range only 2.7 mm/day. The simulation results of model data show that except for the underestimation in the northeastern corner, the range in other regions of most models is higher than that of observational data; a few models, such as MPI-ESM1-2-LR, show widespread underestimation. Most models have a strong negative correlation with observational data. Among them, the correlation coefficients of CNRM-CM6-1 and CMCC-CM2-HR4 both exceed 0.5, showing a significant negative correlation, while model BCC-CSM2-MR shows the strongest positive correlation, with a correlation coefficient of 0.49, which can well simulate the spatial distribution characteristic of "small range in the northwest and large range in the southeast."

3.3. Spatial Variability

To explore the uniformity of precipitation spatial distribution and evaluate the simulation effect of climate models on precipitation spatial distribution, the standard deviation between simulation results and observational data is compared to judge the ability of models to capture precipitation spatial variability. The standard deviation of observational data is large in southern Tanzania, indicating significant annual precipitation differences in this region; the standard deviation is relatively small in the central and northern parts, with stable precipitation. From the spatial distribution map of model data, it can be seen that most models can reproduce the characteristic of uniform precipitation distribution in the northeastern corner of Kenya, but there are obvious deviations. The spatial distribution of most models shows underestimation in the eastern and northeastern parts and overestimation in other parts, while NESM3 and MPI-ESM1-2-LR show widespread underestimation in Kenya and Tanzania. The correlation coefficients of BCC-CSM2-MR, CMCC-CM2-HR4, CanESM5, HadGEM3-GC31-MM, INM-CM5-0, MPI-ESM1-2-LR, and NESM3 all exceed 0.5 and are statistically significant. Among them, NESM3 has the highest correlation, with a correlation of 0.76 with the spatial distribution of the standard deviation of observational data. However, a very small number of models have limited simulation capabilities, such as MCM-UA-1-0, whose correlation coefficient with observational data is as low as 0.112. In general, the models can basically simulate the spatial distribution of the annual precipitation standard deviation, but compared with observational data, most models overestimate the western part of the study area and underestimate the northeastern or eastern parts.

4. Seasonal Changes

The study area belongs to a bimodal rainy season region, with precipitation concentrated in the long rainy season (March-May, MAM) and the short rainy season (October-December, OND). Therefore, to evaluate the ability of CMIP6 models to simulate seasonal precipitation, the precipitation characteristics of the long and short rainy seasons between models and observational data are mainly compared.

4.1. Long Rainy Season (MAM)

From the observational data, except for the northeastern part, the precipitation in other regions is abundant. The northwestern part and southeastern Tanzania are high-value areas, with the highest value reaching 5.58 mm/day. Precipitation in a small area in the northeastern part is concentrated between 2 and 2.5 mm/day, with the lowest value of 1.92 mm/day. From the spatial distribution of multiple model data, a few models show widespread underestimation compared with observational data, such as MPI-ESM1-2-LR, CMCC-CM2-HR4, CNRM-CM6-1, and MRI-ESM2-0; model INM-CM5-0 shows overall overestimation, with only a small area in the northeastern corner

underestimating precipitation in the long rainy season. From the perspective of correlation, except for BCC-ESM1, MCM-UA-1-0, and MIROC6, the correlation coefficients between the average precipitation of the long rainy season and observational data all exceed 0.6 and are significantly correlated. Among them, BCC-CSM2-MR, CESM2-WACCM, GFDL-ESM4, and INM-CM5-0 perform excellently in simulation, with correlation coefficients exceeding 0.8.

During the long rainy season, the range distribution of observational data is relatively uniform but generally large, with the maximum range (5.88 mm/day) in the northwest corner, indicating significant temporal precipitation changes in this region, which is prone to severe precipitation fluctuations, especially in small areas in the western and northwestern parts. The simulation results of model data on the range are generally large and show significant regional differences: the northeastern part tends to underestimate the precipitation range, and some models also show underestimation in the southern part, such as CMCC-CM2-HR4, HadGEM3-GC31-MM, and MPI-ESM1-2-LR. Most models have a negative correlation with observational data, among which the negative correlation coefficients of CMCC-CM2-HR4 and NorCPM1 with observational data exceed 0.5. In addition, the spatial distribution of the range size of model data is roughly opposite to that of observational data, indicating that their overall simulation effect on precipitation variability is poor.

The standard deviation field can reflect the inhomogeneity and variability of precipitation in spatial distribution. From the spatial distribution of the standard deviation in the long rainy season, it can be seen that the standard deviation of observational data in the long rainy season is basically below 1 mm/day in the entire region, with uniform overall precipitation changes and no areas with obvious variability. However, only a small number of model simulation results are consistent with observations, such as FIO-ESM-2-0 and NESM3, but their correlation is weak. Most models have poor correlation with observational data, and some even show negative correlation. Most models have a high-value concentration area in northwestern Uganda, with large precipitation variability, indicating unstable precipitation in the long rainy season, while CESM2-FV2 and MCM-UA-1-0 overestimate the overall standard deviation, with high standard deviation in the entire region, indicating strong variability in the entire region.

4.2. Short Rainy Season (OND)

The spatial distribution of observational data in the short rainy season shows that the spatial distribution of precipitation in the short rainy season is similar to that in the long rainy season: the western border has the most abundant precipitation, the southern part has slightly lower precipitation, the northeastern part is still a region with less precipitation, and the central precipitation is slightly lower than that in the long rainy season. The minimum average precipitation in the study area is 1.17 mm/day in the northern part, and the maximum is 5.34 mm/day in the western part. From the spatial distribution of the average precipitation of model data in the short rainy season, most models show an overestimation state, with the average precipitation in the entire region reaching 3 mm/day or above; A small number of models show north-south differences, such as CESM2-FV2 and NorCPM1, which show underestimation in the south and overestimation in the north, while NESM3 shows the opposite, with underestimation in the north and overestimation in the south; some models show east-west differences, such as CESM2-WACCM and MPI-ESM1-2-LR, which are roughly underestimated in the east and overestimated in the west or southwest, while CNRM-CM6-1 shows the opposite, with underestimation in the west and overestimation in the east. From the perspective of correlation, the simulation effects of models show a two-level difference: the spatial correlation coefficient between well-performing models and observational data is as high as around 0.9, among which CMCC-CM2-HR4 even reaches 0.92, while CESM-FV2 and CNRM-CM6-1 have poor simulation effects, with correlation coefficients less than 0.4, and cannot effectively reproduce the spatial characteristics of observational data.

The contrasting performance in the short rainy season simulation—with CMCC-CM2-HR4 achieving 0.92 correlation and CNRM-CM6-1 below 0.4—suggests that model performance is highly

season-dependent, which is crucial for regional drought/flood early warning, as East Africa's agriculture relies heavily on both rainy seasons.

During the short rainy season, the spatial distribution of the range of observational data is significantly smaller than that in the long rainy season, indicating that the overall precipitation variability in the short rainy season is lower than that in the long rainy season, and the probability of extreme precipitation events is also relatively low. Similar to the long rainy season, the range in the northwest corner is still large in the short rainy season. The simulation results of model data show that the underestimation areas are mainly concentrated in the eastern part, but some models still show widespread underestimation, such as FIO-ESM-2-0, MPI-ESM1-2-LR, and NESM3, among which NESM3 shows underestimation in the entire region. Some models have a negative correlation with the range of observational data, but the correlation coefficients are generally small. Among them, BCC-ESM1 has the strongest negative correlation, with a correlation coefficient of -0.4, indicating that its spatial distribution of range is roughly opposite to that of observational data; while MRI-ESM2-0 has a high correlation with observational data, with a correlation coefficient exceeding 0.5, but in the northeastern and northwestern parts, the simulated range values are significantly higher, overestimating the risk of extreme precipitation events.

The standard deviation in the entire region during the short rainy season is generally lower than 1.5 mm/day, with relatively uniform precipitation changes. The standard deviation is higher in the southern and eastern parts and lower in the northwestern part, and the precipitation stability in the northwest border is the best. From the simulation results of model data, most models show overestimation in the western part and frequent underestimation in the eastern or northeastern parts; some models show overall overestimation, such as GFDL-ESM4; some models show widespread underestimation, such as MPI-ESM1-2-LR and NESM3.

4.3. Taylor Analysis

Taylor analysis shows the similarity between the simulation results of annual average precipitation, average precipitation in long and short rainy seasons, and observational data. Most of the correlation coefficients between model data and observational data for annual average precipitation are in the range of 0.6-0.9, with good overall simulation effect; the variability of simulation results is concentrated around 0.5-1.5. Combining root mean square error (RMSE) and standard deviation, the models that match well with observational data are BCC-CSM2-MR, CESM2-WACCM, CMCC-CM2-HR4, FIO-ESM-2-0, and INM-CM5-0. Among them, INM-CM5-0 is regarded as the model with the best match with observational data because it has the shortest straight-line distance from the observation reference point.

Most of the correlation coefficients between model data and observational data are in the range of 0.5-0.85. The standard deviation of most model simulation results is higher, indicating a higher degree of spatial deviation of precipitation. The RMSE and standard deviation of BCC-CSM2-MR and MPI-ESM1-2-LR are close to those of observational data; relatively speaking, BCC-CSM2-MR has a higher correlation coefficient, so BCC-CSM2-MR is the model with the best match with observational data for the average precipitation in the long rainy season.

From the Taylor analysis of the average precipitation in the short rainy season, it can be seen that the correlation coefficients between model simulation results and observational data are relatively scattered, with a large span, ranging from 0.2 to 0.95. The standard deviation of most simulation results is larger than that of observational data, distributed around 1.5 or above, which tends to overestimate extreme precipitation in some areas. The well-performing models include BCC-CSM2-MR, CMCC-CM2-HR4, MPI-ESM1-2-LR, and MCM-UA-1-0. Among them, the RMSE of MCM-UA-1-0 is about 0.7, which is smaller than that of BCC-CSM2-MR and CMCC-CM2-HR4 with observational data; while BCC-CSM2-MR and CMCC-CM2-HR4 have large correlation coefficients with observational data, but these two models have poor stability. Therefore, MCM-UA-1-0 is the model with the best overall match with observational data for the average precipitation in the short rainy season.

The SPI (Standardized Precipitation Index) time series in the long rainy season shows that the overall SPI of observational data in the long rainy season presents a significant downward trend, tending to aridification, and the SPI value is basically maintained in the range of -2 to 2. The observational data show that extreme drought occurred in the study area during the long rainy season in 2001, with SPI lower than -2. Among the model data, most show an aridification trend but do not pass the significance test; some show a slight upward trend opposite to the observational data trend, such as BCC-CSM2-MR, FIO-ESM-2-0, GFDL-ESM4, HadGEM3-GC31-MM, INM-CM5-0, and MCM-UA-1-0. Among them, only BCC-CSM2-MR shows a significant upward trend, indicating an upward trend of precipitation from 1979 to 2014, which is an overestimation of precipitation compared with observational data, but other linear upward trends are not obvious. The SPI of model data fluctuates widely in the long rainy season, with multiple extreme drought and flood events. For example, model NorCPM1 shows that the study area presented an extreme wet state during the long rainy season in 1996, with an SPI value close to 4.

The overall trend of observational data SPI is stable, with a slight downward trend of precipitation. Extreme drought and flood events occurred during 1998-2008. For model data BCC-CSM2-MR, CESM2-FV2, CESM2-WACCM, GFDL-ESM4, and NorCPM1, most extreme drought and flood events occurred before 1994; although there were fluctuations in the later period, the overall trend was stable. The simulation performance of model data for extreme drought and flood is poor, and some models overestimate seasonal precipitation with large fluctuation ranges. Model data from EC-Earth3-AerChem, INM-CM5-0, and NorCPM1 show a significant upward trend, and the simulation results show that the short rainy season tends to be humid.

5. Interannual Changes

The observational data show that the overall precipitation presents a significant aridification trend: there were few extreme drought events before 1997 (only SPI < -2 in June 1990), and extreme wet months were more frequent; after 1997, extreme drought and flood events occurred frequently, reflecting a significant increase in precipitation variability. The simulation results of model data show that the trends of most models are not significant, and only CNRM-CM6-1, CanESM5, and NorCPM1 show significant trends. Among them, only CNRM-CM6-1 shows an aridification trend, while CanESM5 and NorCPM1 show a significant humidification trend.

This discrepancy—with only CNRM-CM6-1 simulating the observed aridification while others show humidification—raises concerns for climate projection reliability, as accurate interannual trend simulation is essential for long-term water resource planning in East Africa.

In the observational data, the contribution rate of the first eigenvector is 55.7%, with high explanatory power for precipitation variation distribution. It can be seen from the figure that the entire study area has positive values, indicating that the precipitation changes in the study area have the consistent characteristic of "simultaneous increase or decrease"; the high-value area is located in the area near the Indian Ocean at the junction of Kenya and Tanzania, where the precipitation change amplitude is significantly higher than that in other regions; the eigenvalue gradually decreases from the high-value area in the central and eastern parts to the northwestern and southern land areas, forming a spatial pattern of "high in the central and eastern parts and decreasing around." Among the model data, except for CESM2-FV2, the variance contribution rates of other models are lower than that of observational data. All model spatial eigenvectors show positive values, indicating that they simulate the consistent precipitation distribution characteristic of the entire region, but the specific distribution location of the high-value area is inconsistent with that of observational data: most high-value centers shift to the northwest, concentrated at the junction of the three countries or even the northwest highlands; the model data CESM2-FV2, which has the highest modal variance contribution rate, has an abnormally high-value area in the northwest, and the area of the high-value area of CESM2-FV2 is significantly larger than that of the observation. The correlation coefficients of CNRM-CM6-1, CanESM5, FIO-ESM-2-0, and NESM3 exceed 0.6, among which FIO-ESM-2-0 has

the highest correlation coefficient with observational data, reaching 0.7, indicating that its simulation effect is the closest to observational data among the measured model data. The lowest correlation coefficient is MCM-UA-1-0, with a correlation coefficient of only 0.006 with observational data; its high-value area is completely misplaced to the northwest, which is significantly different from the observed high-value area along the Indian Ocean coast.

The slope of the fitted line of the time coefficient of observational data is negative and significant, indicating that the precipitation in the study area showed a decreasing trend from 1979 to 2014; the time coefficient reached the maximum in February 1998, corresponding to more precipitation in the region, while it reached the minimum in January 1991, which showed an opposite pattern in the study area, with less precipitation in the entire region. Due to the unified standard of spatial modal distribution, the time coefficients between observational data and model data can be directly compared. It can be seen that the slopes of the variation lines of model data CanESM5, FIO-ESM-2-0, INM-CM5-0, and NorCPM1 are significant but opposite to the observed trend, simulating an upward precipitation trend and gradual humidification; although there are also simulation results consistent with the observational data trend, such as BCC-ESM1, CESM2-WACCM, CNRM-CM6-1, MIROC6, MPI-ESM1-2-LR, MRI-ESM2-0, MIROC6, and HadGEM3-GC31-MM, their slopes are not significant, among which CNRM-CM6-1 has the highest similarity with observational data.

From the observational data, the contribution rate of the second eigenvector is 18.63%, and the first and second modes can represent the main precipitation spatial patterns of the region. The observational data show a north-south inverse distribution pattern in the study area, indicating that the precipitation changes in the region are "less in the south and more in the north" or "more in the south and less in the north"; the dividing line is roughly east-west, with obvious regional division characteristics, roughly in the regions of Kenya, Uganda, and Tanzania, and the areas of positive and negative value regions are equivalent. Among the model data, the simulation effect of the second mode is better than that of the first mode: most models maintain the north-south inverse distribution, and the positive and negative values gradually increase towards the north and south. Only a few models show a counterclockwise shift of the dividing line in the simulation results, presenting a northwest-southeast inverse distribution pattern, such as BCC-ESM1, CMCC-CM2-HR4, CanESM5, FIO-ESM-2-0, MCM-UA-1-0, and MIROC6. Among them, MCM-UA-1-0 shows an obvious two-level distribution area in the northwest-southeast direction: the precipitation in the northwest corner is 2 mm/day higher than the average, and the precipitation in the southeast corner is 2 mm/day lower than the average, or vice versa. The model spatial modes all show high correlation with observational data; the best simulation effects are NESM3 and EC-Earth3-CC, with correlation coefficients exceeding 0.96; the lowest is MCM-UA-1-0, with a correlation coefficient of approximately 0.68.

From the observational data, the time coefficient of the second mode shows an overall upward trend, indicating that the precipitation in the northern part of the observational data increases and that in the southern part decreases; the time coefficient reached the maximum in December 1997, corresponding to the most typical modal characteristic of increased precipitation in the northern part and decreased precipitation in the southern part. From the simulation results of model data, some models show a trend opposite to that of observational data, such as CESM2-WACCM, GFDL-ESM4, INM-CM5-0, MIROC6, MPI-ESM1-2-LR, and NESM3, showing a trend of decreased precipitation in the northern or northwestern part and increased precipitation in the southern or southeastern part. To sum up, EC-Earth3-CC performs the best in the second mode.

6. Results and Discussion

This study comprehensively evaluates the performance of 19 CMIP6 models in simulating precipitation over East Africa from 1979 to 2014. The results reveal significant inter-model variability in capturing climatological mean, seasonal, and interannual precipitation characteristics.

Most models reasonably simulate the overall spatial pattern of precipitation but exhibit regional biases—overestimation in the west and underestimation in the northeast. The best-performing models

(e.g., INM-CM5-0, BCC-CSM2-MR) show high spatial correlations (>0.8) with observations, while others (e.g., CNRM-CM6-1) perform poorly. The simulation of precipitation range and standard deviation further highlights model deficiencies in capturing regional variability, particularly in areas prone to extreme events.

Model performance varies significantly between the long (MAM) and short (OND) rainy seasons. For instance, CMCC-CM2-HR4 excels in OND (correlation ≈ 0.92) but not necessarily in MAM. This season-dependent performance underscores the need for cautious model selection in seasonal forecasting and agricultural planning, given East Africa's heavy reliance on both rainy seasons.

Only a few models (e.g., CNRM-CM6-1) capture the observed drying trend, while others simulate unrealistic wetting trends. The misrepresentation of interannual variability and extreme events (e.g., SPI values) raises concerns about the reliability of long-term projections for water resource management and disaster preparedness.

The first two eigenvectors explain a substantial portion of precipitation variability, but models often misplace the high-value centers or distort the north-south dipole pattern. Such discrepancies may stem from inadequate representation of key climate drivers (e.g., ENSO, IOD) in the models.

The findings emphasize that while some CMIP6 models demonstrate skill in simulating certain aspects of East African climate, no single model performs best across all metrics. Multi-model ensembles and bias correction techniques may improve reliability. Future work should focus on model improvement regarding regional processes and extreme event simulation to enhance climate resilience in East Africa.

7. Conclusion

The evaluation of CMIP6 models highlights significant variability in their ability to simulate precipitation patterns in East Africa. While some models perform well in capturing spatial and seasonal trends, others exhibit substantial biases, particularly in interannual variability. These findings emphasize the need for improved model accuracy to enhance drought and flood prediction capabilities in the region. Future research should focus on addressing these limitations to support effective climate adaptation strategies.

References

[1] Ogwang, B.A., Chen, H., Tan, G., et al. Diagnosis of East African climate and the circulation mechanisms associated with extreme wet and dry events: a study based on RegCM4. Arabian Journal of Geosciences, 2015 8: 10255-10265.

[2] Ongoma, V., Chen, H. & Omony, G.W., Variability of extreme weather events over the equatorial East Africa, a case study of rainfall in Kenya and Uganda. Theoretical and Applied Climatology, 2018, 1: 295-308.

[3] Ojara, M.A., Yunsheng, L., Babaousmail, H., et al. Trends and zonal variability of extreme rainfall events over East Africa during 1960–2017. Natural Hazards, 2021 1: 33-61.

[4] Mulugeta, M., Aster, G., Abrham, A., et al. Multi-century tree-ring precipitation record reveals increasing frequency of extreme dry events in the upper Blue Nile River catchment. Global Change Biology, 2017, 23(12): 5436-5454.

[5] Gebrechorkos, S.H., Hülsmann, S., Bernhofer C., Changes in temperature and precipitation extremes in Ethiopia, Kenya, and Tanzania. International Journal of Climatology, 2019, 39(1): 18-30.

[6] Schmocker, J., Liniger, H.P., Ngeru, J.N., et al. Trends in mean and extreme precipitation in the Mount Kenya region from observations and reanalyses. International Journal of Climatology, 2016, 36(3): 1500-1514.

[7] Federal Ministry of Transport, Visualize and Download GPCC Product, 2025/9/3, https://opendata.dwd.de/climate_environment/GPCC/html/download_gate.html

[8] Earth System Grid Federation, 2025/9/3, https://esgf-node.llnl.gov/search/cmip6/