Comparison of CMIP6 and CMIP5 models in simulating mean and extreme precipitation over East Africa

Brian Ayugi1,2,3 | Jiang Zhihong2 | Huanhuan Zhu2 | Hamida Ngoma2,4 | Hassen Babaousmail5 | Karim Rizwan2 | Victor Dike6,7

1Jiangsu Key Laboratory of Atmospheric Environment Monitoring and Pollution Control, Collaborative Innovation Center of Atmospheric Environment and Equipment Technology, School of Environmental Science and Engineering, Nanjing University of Information Science and Technology, Nanjing, China
2Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environment Change (ILCEC)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing, University of Information Science and Technology, Nanjing, China
3Organization of African Academic Doctors (OAAD), Nairobi, Kenya
4Department of Geography, Geoinformatics and Climatic Sciences, Makerere University, Kampala, Uganda
5Binjiang College of Nanjing University of Information Science and Technology, Wuxi, Jiangsu, China
6International Center for Climate and Environment Sciences, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, China
7Energy, Climate, and Environment Science Group, Imo State Polytechnic Umuagwo, Owerri, Imo State, Nigeria

Correspondence
Jiang Zhihong, Key Laboratory of Meteorological Disaster, Ministry of Education (KLME)/Joint International Research Laboratory of Climate and Environment Change (ILCEC)/Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing, University of Information Science and Technology, Nanjing, China. Email: zhjiang@nuist.edu.cn

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Abstract
This study examines the improvement in Coupled Model Intercomparison Project Phase Six (CMIP6) models against the predecessor CMIP5 in simulating mean and extreme precipitation over the East Africa region. The study compares the climatology of the precipitation indices simulated by the CMIP models with the CHIRPS data set using robust statistical techniques for 1981–2005. The results display the varying performance of the general circulation models (GCMs) in the simulation of annual and seasonal precipitation climatology over the study domain. CMIP6 multi-model ensemble mean (hereafter MME) shows improved performance in the local annual mean cycle simulation with a better representation of the rainfall within the two peaks, especially the MAM rainfall relative to their predecessor. Moreover, simulation of extreme indices is well captured in CMIP6 models relative to CMIP5. The CMIP6-MME performed better than the CMIP5-MME with lesser biases in simulating Simple Daily Intensity Index (SDII), consecutive dry days (CDD), and very heavy precipitation days >20 mm (R20mm) over East Africa. Remarkably, most CMIP6 models are unable to simulate extremely wet days (R95p). Some CMIP6 models (e.g., NorESM2-MM and CNRM-CM6-1) depict robust performance in reproducing the observed indices across all analyses. OND season shows wet biases for some indices (i.e., R95p, PRCPTOT), except for SDII, CDD, and R20mm in CMIP6 models. Consistent with other studies, the mean ensemble performance for both CMIP5/6 shows better performance as compared with individual models due to the cancellation of some systematic errors in the
individual models. Generally, CMIP6 depicts improved performance in the simulation of MAM rainfall compared with CMIP5 models. However, the new model generation is still marred by uncertainty, thereby depicting unsatisfactory performance over the East Africa domain. This calls for further investigation into the sources of persistent systematic biases and a methodology for identifying individual models with robust features that can accurately simulate observed patterns for future usage.

**KEYWORDS**
climate extremes, CMIP5/6, East Africa, evaluation, precipitation

## 1 | INTRODUCTION

The 21st century has witnessed unprecedented occurrences of extreme weather events that adversely affect every component of societal infrastructure and natural ecosystems (Rogelj et al., 2018; Krasting et al., 2018). Nations in the tropics that are characterized by high-temperature occurrence continue to bear the brunt of climate change, characterized by incidences such as acute drought and floods, wildfires, tropical cyclones, and heatwaves, and so forth. (IPCC, 2014). Regions that were predominately considered ‘safe havens’ have been hit by far-reaching impacts of anomalous climate events, thereby weakening their economy and resilience to cope with the situations (Dahinden et al., 2017; Madakumbura et al., 2019). If such patterns are not accurately forecasted and projections of how they will evolve as a result of climate change are not considered reliable, then catastrophic impacts leading to massive loss of human lives and property will be the ‘new norm’. This calls for all relevant stakeholders to devise possible measures and solutions to minimize any potential damages.

The scientific community continues to play a critical role in providing timely and accurate information regarding the evolution of climate extremes. The general circulation models (GCMs) play a vital role in enhancing our understanding of the climate systems. The GCMs have been utilized extensively to investigate the past and future changes in climate variables, particularly precipitation. The output of these models informs relevant stakeholders on the formulation of effective and sustainable policies for mitigation and adaptations to the impact of climate change. The steady progress from the first experiments conducted in a bid to enhance our knowledge of the complex earth system to the latest sixth phase (CMIP6) has witnessed remarkable improvement (Eyring et al., 2016). Consequently, numerous studies have been conducted across various regions using the Coupled Model Intercomparison Project (CMIP) outputs in an attempt to understand, attribute, and/or simulate various aspects of climate systems (Brunner et al., 2020; Fan et al., 2020; Li et al., 2021). Nevertheless, notable challenges have been observed in various outputs of CMIP data sets over different regions (Bador et al., 2020; Forster et al., 2020; Tokarska et al., 2020).

As a way forward, CMIP6 models include many improvements relative to previous generations (Eyring et al., 2016). Higher spatial resolution (~70 km) in comparison to coarser resolution (~250 km) for CMIP5 characterizes the current model generation. Besides improved physical processes and biogeochemical cycles, new features such as the improved representation of aerosols’ effect or refined parameterization schemes, and large ensemble size members are among the developments that characterize the latest model outputs. Subsequently, large volumes of research outputs based on CMIP6 have highlighted notable improvements in modelling various aspects of climate systems (Mauritisen et al., 2019; Voldoire et al., 2019; Hajima et al., 2020; Moseid et al., 2020).

Studies focusing on simulations or projection of mean and extreme climate based on CMIP6 (e.g., Grose et al., 2020; Jiang et al., 2020; Almazroui et al., 2020a, 2020b; Akinsanola et al., 2021; Klutse et al., 2021) or comparative studies of CMIP6 against CMIP5 performance have also reported better and more reliable results (Nie et al., 2019; Gusain et al., 2020; Jiang et al., 2020; Luo et al., 2020; Seneviratne and Hauser, 2020; Zamani et al., 2020; Zhu et al., 2020), Chen et al. (2020), while equating the performance of CMIP6 to CMIP5 in the simulation of climate extremes, noted a significant reduction in the model spread among the CMIP6 models compared with CMIP5, particularly over regions in the northern latitudes. Mainly, the study observed more distinct projections of very heavy precipitation days above 20 mm (R20mm) and maximum consecutive 5-day precipitation (RX5day) than in CMIP5 simulations.

Conversely, a regional study conducted using CMIP6 across 41 sub-regions globally, as delineated for the
upcoming IPCC assessment report six (AR6; Iturbide et al., 2020) reveals limited improvements compared to the CMIP5 models (Kim et al., 2015). Interestingly, the study shows persistent systematic biases (i.e., cold biases) in cold extremes over high-latitude regions. Nonetheless, simulation of precipitation extremes shows an improved model skill in CMIP6 for the indices denoting intensity and frequency with evidently reduced biases. The aforementioned studies continue to show varying results in the simulations of mean or extreme climate events in CMIP6 as compared with the predecessor. These studies continue to enhance our understanding of the suitable models to be used for accurate diagnosis and projection of impact analysis.

Over East Africa (Figure 1), the livelihood of its population is from weather and climate-dependent sectors. The sectors are under threat posed by pronounced changes in the climate system, mainly due to an increase in mean surface temperature and reduction in precipitation (Shongwe et al., 2011; Seneviratne et al., 2012; Niang et al., 2014; Gebrechorks et al., 2018, 2019; Krasting et al., 2018; Ayugi et al., 2019; Ngoma et al., 2021a). The destructions witnessed over recent years are threatening the economy and ecosystem (IPCC, 2014). For instance, recurrent droughts (Nicholson, 2014; Haile et al., 2020; Ayugi et al., 2020a, 2020b) and floods (Kilavi et al., 2018; Juma et al., 2020) remain the signature features affecting millions of people and have a negative impact on the gross domestic product in the region that is mainly dependent on the agrarian economy (World Bank, 2012; FAO, 2019). Studies characterizing observed events have been based on various reanalysis or satellite-derived data sets with clear patterns observed and hotspots identified (Liebmann et al., 2014; Lyon, 2014; Gebremeskel et al., 2019). Projection studies of mean and extremes climate have been conducted using the available GCMs from CMIP3/5 (Shongwe et al., 2011; Otieno and Anyah, 2013a, 2013b; Ongoma et al., 2018a, 2018b) or dynamically downscaled regional data sets (RCMs) (Osima et al., 2018; Ogega et al., 2020; Onyutha, 2020; Ayugi et al., 2020a).

**Figure 1** Location of East Africa (enclosed in black rectangle) in Africa along longitudes 28–42° E and latitudes 12–5° N (a) and (b) shows elevation (m) and physical features. The digital elevation model (DEM) data sets was obtained from shuttle radar topography Mission (SRTM) 90 m spatial resolution (3 arcsec). The lowest elevation is represented by jungle green in the eastern sides while the highest elevation by light green (Mt Rwenzori in the southwest, Mt Elgon in the east, and Mt Kenya in the Central Kenya region) [Colour figure can be viewed at wileyonlinelibrary.com]
As witnessed across other regions, the discrepancies in CMIP5 or RCMs are equally recognized in studies that have been based on such data sets over the EA domain (Kent et al., 2015; Rowell et al., 2015; Yang et al., 2015; Kisembe et al., 2018; Ongoma et al., 2018a). Few studies have employed the latest CMIP6 model outputs to examine their capability in simulating the observed extreme events nor projecting the possible future incidences over the region (Akinsanola et al., 2021). The aforementioned study examined the capability of CMIP6 models in simulating the statistics of extreme precipitation over the EA region and reported a better performance of MME in representing observed precipitation extremes. However, the study noted consistent biases across various CMIP6 models, which tend to overestimate the total-wet day precipitation and consecutive wet days. Presently, no study has established the specific value-added by to the CMIP6 models relative to CMIP5 versions over the study locale. The improved performances illustrated over various domains [i.e, South Asia: Iqbal and Zahid, 2014; Central Asia: Guo et al. (2021); and Iran: Zarrin and Dadashi-Roudbari (2021), etc.], gives a promise of accurate and reliable projections of future climate in a region that demonstrated paradox patterns during the long rainy season (Rowell et al., 2015).

The overall aim of this paper is to reveal the ability of CMIP6 GCMs in simulating the climate over East Africa and compare their performance with that of CMIP5 GCMs. The specific questions to address are: (a) To what extent can the CMIP6 GCMs reproduce the observed mean climatology and seasonal rainfall extremes over EA region? and (b) Do the CMIP6 GCMs have the advantages over their CMIP5 predecessors? The rest of the paper is organized as follows: details of data and techniques used are explained in Section 2 while results are presented in Section 3. Discussions are presented in Section 4. Lastly, the conclusions and recommendations are highlighted in Section 5.
2 | DATA AND METHODS

2.1 | Model outputs and observations

This study uses 13 historical simulations of CMIP6 (Eyring et al., 2016) and equal number for the CMIP5 (Taylor et al., 2012) obtained from an open-source platform available at https://esgf-node.llnl.gov/projects/esgf-llnl. The details regarding the data set's structures are presented in Table 1. A summary table highlighting the notable advances in the CMIP6 as compared with the precursor version is presented in Table 2. To enable intercomparison, only first member realization outputs (r1i1p1f1) for CMIP6 and r1i1p1 for CMIP5 are utilized in this study, despite the large ensemble members available in CMIP6 data sets. Preliminary analyses based on the first three ensemble members for NorESM1-M and NorESM2-MM of CMIP5/6, respectively indicated that the models were not sensitive to the ensemble member selected. In fact, the correlation analysis indicated no statistically significant differences between the ensemble members and the mean precipitation obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS version 2) data sets. Hence, the choice for the first ensemble for all models.

The (CHIRPS; Funk et al., 2015) is used as observed data owing to its superior performance over the study region as compared to other existing data sets (Kimani et al., 2017; Cattani et al., 2018; Dinku et al., 2018; Gebrechorkos et al., 2018; Ayugi et al., 2019). Many studies have pointed out insufficient reliable in situ data sets that can be used for weather and climate studies over the EA region (Camberlin and Okoola, 2003; Su et al., 2008). The advent of alternative sources such as satellite-derived or reanalysis data sets has played a critical role as a substitute source for climate estimates. In this paper, all data sets are aggregated to a uniform temporal scale of 1981–2005 and the lowest spatial resolution of the models using the bilinear remapping technique.

2.2 | Climate indices

This study uses extreme climate indices developed by the Expert Team on Climate Change Detection and Monitoring Indices (ETCCDMI). The listed indices mainly consider aspects of extreme intensity, frequency, and duration of precipitation events over the study area (Klein Tank et al., 2009; Zhang et al., 2011). The indices can be divided into four main classes. Firstly, the duration indices, which mainly define periods of excessive wetness/dryness. Here we used consecutive dry days (CDD) that represent the extent of the most prolonged dry anomaly in a year, characterizing the possible drought occurrence. Secondly, a percentile-based index that defines very wet days (R95P). The precipitation index used in this classification represents the rainfall amount falling above the 95th (R95p). The threshold-based index (the number of days when precipitation quantity is above or below a fixed threshold) is based on the exceedance of very heavy precipitation days where rainfall >20 mm (R20). Lastly, the study used indices that delineate the period of the seasonal precipitation total (PRCPTOT) and those that define precipitation intensity, such as the simple daily intensity index (SDII). Details regarding the indices are provided in Table 3.

2.3 | Evaluation techniques

Various multi-model statistics such as spatial coefficient correlation (SCC), spatial standard deviation (SSD), and spatial variation of root-mean-square error (RMSE) are used to assess the overall skills of models simulating the observed extreme events during two main rainy seasons (i.e., March to May [MAM] and October to December [OND]) over the study area. It should be noted that a unimodal pattern, with most rainfall occurring during December to April, is experienced over Tanzania region while regions in the north of equator is mostly during June to August (Dunning et al., 2016). The widely used metrics are summarized using Taylor diagrams (TD; Taylor, 2001). The value of SCC close to 1 denotes perfect positive model performance while −1 shows the inability of models to reflect the observed features. Conversely, the perfect representation of RMSE is depicted by 0 and that of SSD is 1. Recent approach of model ranking, also known as Taylor skill score (TSS) is used to assess model skill. Taylor (2001) defined TSS as given in Equation (1);

\[ TSS = 4(1 + PC)^2 / \left( \frac{\sigma_{\text{cmip}}}{\sigma_{\text{chirps}}} + \frac{\sigma_{\text{chirps}}}{\sigma_{\text{cmip}}} \right) (1 + PC_0)^2 \] (1)

where PC is the pattern correlation coefficient between the model outputs and observations. The PC0 is the highest PC achievable (here, we set the threshold at 1). Variable such as \( \sigma_{\text{cmip}} \) and \( \sigma_{\text{chirps}} \) represent SSD of the simulated and observed patterns, respectively. The score ~ 1 threshold value shows a perfect association between model and observations whereas 0 expresses contrary model performance. Successful application of this technique has been demonstrated in various studies (e.g., Wang et al., 2018; Luo et al., 2020; Xin et al., 2020; Zhu et al., 2020; Ngoma et al., 2021b). We assess the grid points where changes were statistically significant at 95% using a two-tailed Student t test.
TABLE 2  Simple introduction of the updates of CMIP6 models compared with that in CMIP5

| Models                  | Institute, country                          | Atmospheric resolution | Major improvements                                                                                                                                                                                                 | References       |
|-------------------------|---------------------------------------------|------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------|
| ACCESS-ESM1.5/ACCESS1.0 | Commonwealth Scientific And Industrial Research Organization and Bureau of Meteorology (Australia) | 1.25° × 1.875°/1.25° × 1.875° | The improvement in the biogeochemical components for the land and ocean to simulate the global carbon cycle. The model is also the only CMIP6 model with phosphorous limitations on the land, highlighting its unique status. | Ziehn et al., 2019 |
| BCC-CSM2-MR/BCC-CSM1.1-M | Beijing Climate Center (BCC), China          | T42, L26/T106, T46     | Modification of the deep convection parameterization, a new scheme for the cloud fraction and indirect effects of aerosols; significant improvement in surface processes of BCC-AVIM; new schemes for surface turbulent fluxes of momentum, heat, and water | Wu et al., 2019   |
| CanESM5/CanESM2         | Canadian Climate Centre, Canada               | T63, L49/T63, L49      | Completely new models for the ocean, sea ice, and marine ecosystems, and a new coupler                                                                                                                                 | Swart et al., 2019|
| CNRM-CM6-I/CNRM-CM5     | Centre National de Recherches Météorologiques (CNRM) and Cerfacs | 1.4°/T1127,             | Improvement in the mass and energy conservation in the simulated climate system to limit long-term drift. In addition, deep ocean biases are generally reduced, whereas sea ice in the Arctic improved. Sensitivity in rising CO₂ in the model has increased. Lastly is the equilibrium climate sensitivity (4.9 K) is now close to the upper bound of the range estimated from CMIP5 models. | Voldoire et al., 2019|
| FGOALS-g3/FGOALS-g2     | Institute of Atmospheric Physics (IAP), Chinese Academy of Sciences (CAS), China | 2.8° × 3.1°, L26/2.0°, L26 | Improved TSPAS advection; new schemes for the physical process, including the boundary layer, stratiform cloud; A convection momentum transport has been considered                                                                 | Li et al., 2021   |
| INM-CM4-8/INM-CM4       | Institute of numerical mathematics (INM) of the Russian Academy of Sciences, Russia | 2° × 1.5°, L21/2° × 1.5°, L73Akinsanola | A more sophisticated parameterization of condensation and cloudiness formation; incorporating an aerosol module; upgraded oceanic component                                                                 | Volodin et al., 2017|
| IPSL-CM6A-LR/IPSLS-CM5A-LR | Institute Pierre Simon Laplace (IPSL), France | 3.75° × 1.9°, L39/2.5° × 1.3°, L79 | Including new versions of LMDZ, of NEMO and of ORCHIDEE; improved conservation of energy and water; increased resolutions for atmosphere and land-surface, and for ocean                                                                 | Hourdin et al., 2019|
| MIROC6/MIROC5           | The Center for Climate System Research, the University of Tokyo, the Japan Agency for Marine-Earth Science and Technology, and the national institute for environmental studies, Japan | T85, L40/T85, L81      | Incorporating a new parameterization for shallow convective processes; an updated k-distribution scheme for radiative transfer; a new parameterization for non-orographic gravity wave                                                                 | Tatebe et al., 2019|

(Continues)
Model performance metric

Following the approach proposed by Gleckler et al., 2008 and later modified by Sillmann et al. (2013), the metrics technique based on RMSEs of the model climatology pattern is employed in this study. The equation for RMSE is as follows:

$$RMSE_{GO} = \sqrt{\langle (G - O)^2 \rangle}$$  \hspace{1cm} (2)$$

where G and O are denoted as the model and observed climatology of an index, respectively. The angular brackets denote the spatial mean of the study area. The relative CMIP6 (CMIP5) RMSE ($RMSE'_{GO}$) for each model is derived as

$$RMSE'_{GO} = \frac{RMSE_{GO} - RMSE_{median}}{RMSE_{median}}$$  \hspace{1cm} (3)$$

where $RMSE_{median}$ represents the median of the RMSE for all models. $RMSE'_{GO}$ provides an indication of a model’s performance with respect to observed data sets. Negative values for $RMSE'$ indicate that the corresponding model performs better than the majority

| Models          | Institute, country                       | Atmospheric resolution | Major improvements                                                                                                                                                                                                 |
|-----------------|------------------------------------------|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| MIROC-ES2L/MIROC-ESM | National Institute for Environmental Studies, The University of Tokyo (Japan) | T42; L128, 64/L40     | The model’s ocean biogeochemical component has been largely been updated to simulate the biogeochemical cycles of carbon, nitrogen, phosphorus, iron, and oxygen such that primary productivity can be controlled by multiple nutrient limitations. |
| MPI-ESM1-2-HR/MPI-ESM-LR | Max Planck Institute (MPI), Germany       | T63/T127 | New radiation and aerosol parameterizations; introducing a multilayer soil hydrology scheme, extending the land biogeochemistry to include the nitrogen cycle; the ocean biogeochemistry now represents cyanobacteria prognostically |
| MPI-ESM1-2-LR/MPI-ESM-LR | Max Planck Institute (MPI), Germany       | T63; L192,96/L47      | The new radiation and aerosol parameterization of the atmosphere, several relatively large, but partly compensating, coding errors in the model’s cloud, convection, and turbulence parameterizations have been improved. The representation of land processes has been refined by introducing a multilayer soil and litter decomposition model and improving the representation of wildfires. |
| MRI-ESM2-0/MRI-CGCM3 | Meteorological research institute (MRI), Japan | TL159, L48/TL159, L80 | New stratocumulus parameterization; the new stratocumulus scheme; new treatment of the WBF effect |
| NorESM2-MM/NorESM1-M | Norwegian Climate Centre (NCC), Norway   | 1.9° × 2.5°, L26/1.9° × 2.5°, L32 | Improved energy and angular momentum conservation; improved deep convection; improved aerosol handling; new sea-salt emission parameterization; online emissions of mineral dust; improved heterogeneous ice nucleation treatment |

Note: The models from CMIP6 are in bold.
TABLE 3 Definitions and units of precipitation indices employed in this study

| ID    | Name                      | Definitions                                                                 | Units |
|-------|---------------------------|-----------------------------------------------------------------------------|-------|
| PRCPTOT | Wet-day precipitation amount | Total precipitation in wet days (RR ≥ 1 mm), defined as $P_{ij}$ representing daily precipitation amount on day $I$ in period $j$. If $I$ denotes the number of days in $j$, then; $PRCPTOT_j = \sum_{i=1}^{I} P_{ij}$ | mm    |
| R95p | Extremely wet days | Total precipitation when $PP > 95$th percentile. Here, $P_{cd}$ be daily precipitation amount on a wet day ($PP \geq 1.0$ mm) in a period $i$ and let $P_{cd}^{95}$, where 95th percentile of precipitation on wet days in the baseline/projected period. If $d$ represent the number of wet days in the period, then $R95P_j = \sum_{c=1}^{d} P_{cd}$ where $P_{cd} > P_{cd}^{95}$ | mm |
| SDII | Wet-day intensity | Average precipitation from wet-days. This can be defined as $P_{w}$ be the daily precipitation amount on wet days, $w$ ($PP \geq 1$ mm) in period $j$. If $w$ represents number of wet days in $j$, then $SDII_j = \frac{\sum_{i=1}^{w} P_{w}}{w}$ | mm day$^{-1}$ |
| R20mm | Heavy precipitation days | Number of very heavy precipitation days (RR ≥ 20 mm). That is; let $P_{ij}$ be the daily precipitation amount where $PP_{ij} \geq 20$ mm | Days |
| CDD | Consecutive dry days | Maximum number of consecutive dry days (RR ≤ 1 mm). Let $P_{ij}$ be the daily precipitation amount on day $I$ in period $j$. Count the largest consecutive days where $PP_{ij} \leq 1$mm | Days |

| of models. The RMSE values for all models are summarized in a portrait diagram that gives a summary for all individual model performance. The portrait highlights the regional mean RMSE for each index (PRCPTOT, SDII, CDD, R20mm, and R95p) described in rows and for 26-CMIPs models in columns. In this study, precipitation indices are represented by red (blue) colour for CMIP6 (CMIP5). Respectively. The colder colour (negative values) series indicates better performance whilst warmer colour (positive values) denotes models with relatively low skills on average. Moreover, CMIP5/6-MME is equally evaluated and presented in the last two columns of the portrait diagram. More information regarding this approach can be found in Sillmann et al. (2013).

3 | RESULTS

3.1 | Climatology of mean and precipitation indices

As a first step, this study examined the characteristics of the monthly precipitation rate over East Africa as simulated by CMIP6/5 against the observed data. The annual cycle of model simulation and their multimodel ensemble mean in comparison with CHIRPS is presented in Figures 2 and 3. Over EA, CHIRPS demonstrate a bimodal pattern with peaks during MAM and OND (Kimani et al., 2017; Cattani et al., 2018; Ayugi et al., 2019). The months of June–September (JJAS) are relatively dry seasons, with July being the driest, reflecting <1 mm day$^{-1}$ precipitation rate over most of the region. The two peaks showed in the observed data are mostly associated with the tropical rain belt that oscillates from 15°S–15°N throughout the year (Nicholson, 2018). Interestingly, both the CMIP5 and the CMIP6 models reproduced the annual precipitation cycle over East Africa. However, CMIP6 shows improved simulation of the MAM season compared to CMIP5 (Figure 2). Moreover, improvement is further noted in the reproducibility of OND peak (3.21 mm day$^{-1}$) in CMIP6 with notable models such as NorESM2-MM (3.1 mm day$^{-1}$), MPI-ESM1-2-LR (3.23 mm day$^{-1}$), and CNRM-CM6-1 (3.54 mm day$^{-1}$) able to simulate the peak satisfactorily. Comparative analysis of model performance in the simulation of the two peaks for CMIP6 and CMIP5 reveal
varying features. Remarkably, the two model outputs vastly overestimated the OND peaks, with CMIP5 models exhibiting overestimations (Dike et al., 2015; Ongoma et al., 2018a), including the MME (4.73 mm-day\(^{-1}\)) relative to the observed value of 3.21 mm-day\(^{-1}\) (Figure 3). Interestingly, the CMIP6-MME robustly reproduced the bimodal climatology of MAM and OND season, unlike CMIP5-MME. This shows better reproducibility of annual rainfall over the study region by new model generation. On the contrary, OND precipitation shows many wet biases during the recent decades as is well reproduced in both model ensembles (Figures 2 and 3).

Despite the ensemble mean showing an aspect of underestimations (overestimations) for MAM season in CMIP6/5, it outdid most individual models relative to CHIRPS (Figures 2 and 3). However, the OND showed wet bias in both CMIP5/6 ensembles. Typically, the study shows an improved performance in CMIP6 in the local annual mean cycle simulation with a better representation of two peaks, especially the MAM. For instance, the CMIP6-MME simulated MAM rainfall at 3.7 mm-day\(^{-1}\) while CMIP5 had 3.5 mm-day\(^{-1}\), against the observed value of 3.8 mm-day\(^{-1}\). The model NorESM2-MM showed a remarkable performance in the annual cycle simulation over the study area with the value closer to the observations (i.e., 2.65 mm-day\(^{-1}\) against CHIRPS at 2.71 mm-day\(^{-1}\)) (Figure 2). However, the performance of CMIP6 in simulating annual precipitation is found unsatisfactory over Tibetan Plateau Zhu and Yang, 2020). A number of comparative studies across other regions globally equally show varying performances with some studies illustrating improved performance by CMIP6 models and their ensembles means (Xin et al., 2020; Zamani et al., 2020; Zhu et al., 2020).

3.2 Spatial patterns of precipitation extremes

A comparative analysis of model performance in the reproducibility of the observed seasonal climatology of precipitation indices for MAM and OND over the study region is shown in Figures 4 and 5. The spatial distribution of the precipitation biases of five extreme indices used (Table 3) and the respective boxplots are shown for the period 1981–2005. The results show the performance of CMIP6-MME in the simulation of observed extreme events as compared to its predecessor. The model ensemble for MAM season indicates an aspect of underestimation for most indices except for CDD over the study area (Figure 4). The OND season shows overestimation of most precipitation indices except for SDII and R20mm
CMIP5 depicts the largest areal mean relative bias relative to CMIP6 in total precipitation with 28% as compared to 21% in CMIP6 for MAM precipitation. OND shows a smaller areal mean relative bias in CMIP6-MME as compared with its predecessor (Figure 5). Remarkably, the intermodel range for PRCPTOT exhibit decrease between CMIP5 and CMIP6 ensembles for MAM while OND show an increase pattern. Other indices highlight the biases of 8.1% (1.0%) for R95p, SDII (−3.9%) (−4.2), and R20mm (−0.8 days) (−1.0 days) while OND depicts biases of 29.8% (21.6%) for R95p, SDII (−2.2%) (−2.3), and R20mm (0.6 days) (0.1 days) (Figures 4 and 5). This suggests that while the CMIP6 models simulated large biases in PRCPTOT and R95p, the models outperformed the CMIP5 models with lesser negative biases in SDII, R20mm, and CDD (as Figure 4g, j and m illustrate).

In agreement with previous studies (i.e., Osima et al., 2018; Ogega et al., 2020), the GCMs show an underestimation of CDD, and R20mm, especially over eastern Kenya and northeastern Tanzania, where models agree significantly. A related study at the global level (Chen et al., 2020), also observed persistent underestimation of R20mm and CDD in CMIP models. The study attributed the simulated biases in CMIP6 models as compared with CMIP5 models to increased warming in the future. The remarkable negative bias for CDD in CMIP6-MME is mainly as a result of poor simulations by models such as INM-CM4 (26 days) and MIROC-ES2L (30 days) (not shown here). Chen et al. (2020) attributed the notable underestimation of CDD to the increased spatial resolution in CMIP6 models, thereby capturing more precipitation that is often simulated at a much finer scale by high-resolution models. Notably, western Uganda shows a substantial bias of overestimating heavy precipitation days despite underestimating in most regions during MAM (Figure 4k–n), and OND (Figures 5k, l, m, and n). Furthermore, bias in PRCPTOT is exceeding 200 mm, R95p is >40 mm, and −10.8 d−1 for CDD, respectively. This could be due to moist westerlies originating from the Congo basin resulting in enhanced rain during the wet seasons in the north and southwest when other parts of the country are cold and dry (Mchugh, 2004; Kizza et al., 2009).

Numerous studies have pointed the challenge of simulating precipitation compared with temperature (Chen et al., 2020; Jiang et al., 2020; Zhu et al., 2020; Almazroui et al., 2020a). This is mainly associated with model parameterization, especially in regions with complex physiographical features such as East Africa region or challenges related to local mesoscale features such as

![Figure 3](wileyonlinelibrary.com)
lakes, vegetation cover, or large coastline which cause regional heterogeneity (Nikulin et al., 2012). Generally, the comparison between the CMIP6-MME and CMIP5-MME over EA region depicts varying performance with improvement in the simulation of some indices (i.e., SDII, R20mm, and CDD) while no significant improvement is noted in reproducibility of extremely wet days for seasonal precipitation. Essentially, the new models depict small biases, such as PRCPTOT (Figure 4a), during MAM with a lower amplitude of <100 mm as compared with >150 mm in CMIP5-MME. However, the higher amplitude is observed in the simulation of PRCPTOT during OND (Figure 5), with >250 mm in CMIP6-MME relative to CMIP5-MME which exhibits a bias of 200 mm in the simulation of total precipitation. The areal-mean bias has reduced in MAM (OND) by 7% (23%). Interestingly, the dry biases seen in CMIP5-MME over eastern Kenya and southern Tanzania are enhanced in CMIP6-MME with model agreements demonstrated by the significant score for annual precipitation (Figure 4e,f). Remarkably, most regions that portrayed either dry/wet biases are equally revealed in both CMIP6-MME and CMIP5-MME except that the CMIP6-MME showed statistically significant changes at the 95% confidence level in such regions. Substantial dry biases are observed during MAM and OND for SDII with CMIP6-MME depicting
robust changes (Figures 4h,i and 5h,i). Notably, most models show agreement on the significant changes over Kenya and Tanzania region in the simulation of precipitation indices except for R95p in both annual and seasonal performance.

The result of the present study indicates that the CMIP6-MME shows overestimation (underestimation) of PRCPTOT, R95P (SDII, CDD, R20mm) extreme precipitation events over most regions as compared to CMIP5-MME for OND season. Conversely, MAM simulation indicates underestimations of most indices excluding CDD. Particularly, the simulations of SDII, CDD, and R20mm are closer to the observation as compared with the CMIP5 simulation which is an indication that the performance of the CMIP models
varies with extreme precipitation indices. The results show an improvement in seasonal simulation, particularly for MAM season as compared to OND rains over the study region. The systematic overestimation (underestimations) in mean precipitation is equally observed in other similar evaluative studies over the Tibetan Plateau and East Asian Monsoon region (Jiang et al., 2020; Zhu and Yang, 2020).

Figures 6 and 7 present a summary of model performance for MAM (OND) climatology as represented in the Taylor diagram (TD) and TSS for all indices simulated in the present study. The TD highlights the statistical features of individual models and MME of 13 CMIP5 and CMIP6 models relative to the observations. Comparative analysis for seasons shows MAM performance is better than OND (Figure 6). The SCC during MAM season for all indices in CMIP6-MME compared to CMIP5-MME shows a robust simulation of PRCPOT (0.92/0.85), R95p (0.6/0.58), SDII (0.34/0.30), CDD (0.75/0.60), and R20mm (0.6/0.54) (Figure 6). Similarly, the OND season exhibited improved performance, with most models and MME showing satisfactory performance for CMIP6-MME against CMIP5-MME (Figure 7). The SCC for PRCPOT demonstrate performance of (0.93/0.91), R95p (0.4/0.3), SDII (0.40/0.32), CDD (0.95/0.94), and R20mm (0.60/0.62). Interestingly, the SDII (Figures 6, and 7) showed the lowest SCC/SSD (<0.3/<1) for both CMIP6/5 in most individual models, indicating reduced inter-model uncertainty.

Additional examination of the CMIP6/5 models based on TSS shows a better representation of most indices during seasonal climatology in the latest model outputs. Results for MAM (Figure 6) show higher TSS for CMIP6-MME in all indices, while OND demonstrates the unsatisfactory simulation of R20mm and PRCPOT in
CMIP6-MME (Figure 7). Significantly, the R95p demonstrated less skill with TSS value for CMIP5/6 at 0.4/0.44 (Figure 7f). Comparative analysis of CMIP6/5 for PRCPTOT showed a better score in CMIP5-MME for OND while R20mm markedly showed minor improvement during OND season (Figure 7f).

The results show the capability of GCMs to robustly simulate the spatial pattern of most precipitation indices over the study area. CMIP6-MME demonstrates better outputs in the simulation of precipitation indices during the MAM season while varying results are showed for the OND season. Enhanced simulation during the MAM season is demonstrated in CDD, SDII, and R20mm, despite the low spatial correlation. At the same time, total precipitation days and extremely wet days are poorly represented during OND. Overall, the performance of the CMIP6 ensemble demonstrates satisfactory performance in the simulation of most extreme events over the East Africa region compared to CMIP5 models. Simulations for R95p and SDII remain a challenge over EA in CMIP6 models.

3.3 | Model performance metric

A portrait diagram that gives a summary for all individual model performance in simulating the precipitation extremes indices for MAM and OND is presented in Figures 8 and 9 respectively. The majority of the CMIP6 models displayed low performance with most models depicting warmer colours as compared to CMIP5 models (i.e., 0.1–0.5). Analysis for MAM season shows that a few CMIP6 models (e.g., NorESM2-MM, and CNRM-CM6-1) showed robust performance with negative RMSE ($\text{RMSE}_{CGO}$) values for PRCPTOT ($-0.5/-0.1$), R95p ($-0.5/-0.2$), SDII ($-0.4/-0.2$), CDD ($-0.1/-0.2$), and R20mm ($-0.5/-0.1$) (Figure 8). On the other hand, MIROC6 exhibited positive values in indices such as PRCPTOT (0.4), R95p (0.5), SDII (0.3), and R20mm (0.4), indicating the worst performance.

On the other hand, most CMIP5 models exhibited $\text{RMSE}'_{CGO}$ except for MIROC5 that showed a positive value $>0.5$ for most indices (Figure 8). During the OND season...
Figure 9, most CMIP6 models continue to exhibit poor skills, with positive values demonstrated in the simulations of most precipitation indices. The best models that established better capabilities include CNRM-CM6-1 and NorESM2-MM with RMSE\(_{GO}\) values for PRCPTOT (−0.5/−0.5), R95p (−0.5/−0.2), SDII (−0.4/−0.2), CDD (−0.1/−0.1), and R20mm (−0.5/−0.2) (Figure 9). Besides, the models MPI-ESM1-2-HR/LR indicated better competencies with RMSE values > −0.2 for most indices. The worst performance is shown by MIROC6 with values for PRCPTOT (0.4), R95p (0.5), SDII (0.3), and R20mm (0.4) (Figure 9). Comparative analysis indicates improved presentation during MAM relative to OND in the CMIP6 models. CMIP6 models and mean ensemble skilfully simulated CDD during MAM and OND with RMSE\(_{GO}'\) values of −0.2.

Consistent with other studies, the performance of the mean ensemble for both CMIP5/6 shows better performance due to the cancellation of some systematic errors in the individual models (Sillmann et al., 2013). While it is widely expected that the new improvements in the latest model outputs ought to translate to reduced uncertainty, the CMIP6-MME continues to exhibit low performance over the EA region. Predominantly, most models showed weak capabilities in the simulation of some indices in both CMIP5/6. The models that revealed better skills in reproducing the observed extreme occurrences for CMIP6 during MAM rainfall include NorESM2-MM, MRI-ESM2-0, and CNRM-CM6-1 while for CMIP5 are MPI-ESM-LR, MPI-ESM-MR, CNRM-CM5, and MRI-CGCM3 (Figure 8). MIROC6, and ACCESS-ESM1-5 showed unsatisfactory simulation during MAM, and OND for most indices over the study area. Whereas the recent study Akinsanola et al. (2021) did not establish a single model in CMIP6 ensembles that can consistently perform best, this study identified three models (i.e., NorESM2-MM, MPI-SM1-2-HR, and MPI-SM1-2-LR) that showed dependable competence during OND season (Figure 9). The listed CMIP5 models that demonstrate better skills over the study region agree with past studies that utilized similar models in a processed-based analysis (McSweeney et al., 2015; King et al., 2021). Overall, most CMIP6 models are unable to simulate the extremely wet days (R95p) during MAM climatology.

**4 | DISCUSSION**

The present study assesses the performance of the new GCMs of CMIP6 against their predecessor in the simulation of mean annual climatology and extreme events during MAM and OND over the EA region. This was achieved by comparing the GCMs with observational data sets obtained from the Climate Hazards Center (CHIRPSv2). The assessment was conducted in terms of spatial patterns and temporal variability for the period 1981–2005, reflecting the starting year of observed data sets and ending year for CMIP5 ensemble models. The study employed robust skill score techniques such as Taylor diagrams and TSS denoting the spatial variability, and
portrait diagrams depicting the RMSEs for each model. The analysis was mainly based on the MME derived by computing the simple arithmetic mean of individual models for two seasons. Likewise, the study used five subsets of precipitation indices obtained from ETCCDMI.

Our results indicate satisfactory performance by CMIP6 models in simulation of two peaks of MAM and OND season, despite wet biases portrayed by most models. Particularly, MAM rainfall is more robustly simulated in CMIP6 models compared to CMIP5 models (Figure 2). However, relatively dry biases persist in MAM season, with CMIP5/6 showing underestimations. Existing studies have observed the wet (dry) biases during OND (MAM) season over the study domain in CMIP GCMs (Othieno and Anyah, 2013a, 2013b; Yang et al., 2015; Ongoma et al., 2018b; Mumo and Yu, 2020). The pronounced dry biases during MAM (Figures 2 and 3) could be a result of an observed reduction in seasonal precipitation (Funk et al., 2008; Lyon and Dewitt, 2012; Liebmann et al., 2014; Ongoma and Chen, 2017; Ayugi et al., 2018). The exact causation of the dry patterns remains a challenge to accurately identify due to the weak correlation with large-scale SST anomalies (Liebmann et al., 2014; Ngoma et al., 2021c). Summary results from most studies have narrowed to the impact of the west to central Pacific and the western Indian Ocean as the significant contributor to the observed decline (Williams and Funk, 2011; Liebmann et al., 2014; Ayugi et al., 2018; King et al., 2021). The resultant impact of the observed decline has affected many communities that continue to rely on the rainfed agro-based economy as means of livelihood due to the impact of drought increase (Adhikari et al., 2015; Mumo et al., 2018; Ayugi et al., 2020a). Thus, alternative solutions must be devised to cope with the dry patterns reflected in CMIP5 and CMIP6 over the region. With the models’ well-pronounced ability to reproduce the MAM rains, projections of its likelihood will be of great importance to the region’s economy.

On the contrary, wet biases during OND in CMIP5/6 (Figures 2 and 3) results agree with previous findings (Hastenrath et al., 2011; Ongoma and Chen, 2017). Compared with the long rains, the OND is strongly correlated to the meridional and vertical circulation cells in the central Indian Ocean, in addition to the intensified upper-level subsidence over east Africa (Mutai et al., 2012; Nicholson, 2015). The shift of overestimation (underestimation) in OND (MAM) precipitations could be attributed to the collocation of dynamical and thermodynamical factors that impacted the changes in the Indian Ocean against the Atlantic Ocean, resulting in observed flood (droughts) during OND (MAM) (Liebmann et al., 2014; Nicholson, 2015). The ability of models to reflect such changes shows strong skills of models in reproducing East Africa’s climate. Nevertheless, the overestimation of the OND rains could negatively impact farmers if the models are used for seasonal forecasting as they would expect more rainfall, and it turns out to be less than expected.

Assessment of precipitation indices shows enhancement of CMIP6 models in representing MAM rainfall comparable with OND (Figures 4–7). The possible attributions of these results could be associated with aspects of improved spatial resolutions of models (Eyring et al., 2016), that can capture local convective systems that could not otherwise be registered in the previous GCMs that had coarser spatial resolution (Taylor et al., 2012). Most significantly, parameterization in the GCMs plays an essential role in the biases observed from one region to another (Flato et al., 2013; Stouffer et al., 2017). The CMIP5 featured aspects of inability to represent the local climate, which could be attributed to coarser spatial resolutions (Table 1) (Kisembe et al., 2018; Ongoma et al., 2018b; Mumo and Yu, 2020; Ayugi et al., 2020b) and poor parameterization schemes (Table 2) (Crowhurst et al., 2020). The case of overestimation by most CMIP6 models and their respective ensembles (Figures 3 and 5), could be attributed to the systematic biases resulting from intermodel weaknesses in their framework schemes (Tatebe et al., 2019; Voldoire et al., 2019; Wu et al., 2019). Similar results have been observed in related studies conducted over Tibetan Plateau (Zhu and Yang, 2020) and the study domain (Akinsanola et al., 2021).

Notably, the complex geomorphology that distinguishes the Tibetan region is also present in the study area. For instance, the high mountains (e.g., Mt. Kilimanjaro, Mt. Kenya, Mt. Elgon, and Mt. Ruwenzori), with an elevation of >4,000 m.s.l play a significant role in enhancing mesoscale features, which are in turn reflected in models with high resolutions (~ 70 km) (Indeje and Semazzi, 2000; Ogwang et al., 2014). The precipitation indices (i.e., R95p), which persistently remained poorly represented (Figures 4, and 5), show the failure of CMIP6 models to represent extreme wet days in OND season. The findings of this study agree with the recent study of Akinsanola et al. (2021), which evaluated the capabilities of CMIP6 models to simulate the statistics of extreme precipitation over the study locale. The work equally noted the persistent overestimations (underestimations) of PRCPTOT and R95p indices during MAM and OND. Moreover, the wet bias observed in CMIP5 (Figure 5) and reported in previous studies (e.g., Ongoma et al., 2018b) has not improved in the CMIP6 models.

The resultant impact could be detrimental to the local community where climate change effects resulting in
extreme events such as floods lead to the destruction of properties and livelihoods. The unskilful simulation of some indices (i.e., R95p), could be linked to the unsatisfactory performance of individual models (i.e., MIROC6) that demonstrates large biases in the reproducibility of extreme events. The main improvement in the new generation model (MIROC6) is mainly in the model's ocean biogeochemical component that has been primarily updated to simulate the biogeochemical cycles of carbon, nitrogen, phosphorous, iron, and oxygen (Table 2; Hajima et al., 2020).

Despite the robust findings of this study, various limitations are noted, influencing the current results. Examples include the limited number of models evaluated (i.e., 13 models from CMIP5/6), the statistical approach used, and the restricted number of indices considered. Nevertheless, the results point to two main directions. Firstly, the improvement in MAM rains simulation presents a promising future of accurate forecast of future climate. The CMIP5 models and subsequent climate analyses established a climate paradox situation where models showed contrary patterns to the observed scenarios. This caused confusion and a lack of consensus on the future state of the regional climate for suitable policy formulation and adaptation.

On the contrary, the latest models’ inability to accurately simulate some extreme events and persistent wet bias during OND peaks highlights situation uncertainty and calls for in-depth studies on the causation of the inability of models to simulate the short rains peaks successfully. Persistent uncertainty exposes various stakeholders such as policymakers and users of climate information to remain in a state of confusion about the future climate during OND season since the models’ reliability cannot be wholly trusted. This calls for further investigation and attribution studies into the sources of unyielding systematic biases. The overall performance in CMIP6 models over the East African region calls for assessment studies to identify the individual models with robust features to accurately simulate observed patterns for future usage.

5 | SUMMARY AND CONCLUSION

The main findings of the present study can be itemized as follows:

1. The CMIP6 models show improved performance in the simulation of mean and extreme precipitation over East Africa relative to CMIP5 models. Particularly, the CMIP6-MME robustly reproduces the bimodal climatology, relative to CMIP5 models. For seasonal climatology, CMIP6 models exhibit robust performance in the simulation of the MAM season and improved reproducibility of the OND season, with notable models such as NorESM2-MM, CNRM-CM6-1, and MPI-ESM1-2-LR capable of simulating the peak satisfactorily relative to CMIP5. Despite the ensemble mean showing dry biases in both seasons in CMIP6/5, it outdid most individual models to perform better compared with CHIRPS. For instance, the CMIP6-MME robustly simulated the peak of MAM season, unlike CMIP5-MME. This shows better reproducibility of MAM rainfall over the study region by the new model.

2. The performance of CMIP6-MME varies as compared to CMIP5-MME in the simulation of extreme indices. For instance, CMIP6-MME performed better than the CMIP5-MME with lesser biases in simulating SDII, CDD, and R20mm over East Africa. On seasonal analyses, CMIP5 shows a larger area mean relative bias relative to CMIP6 in total precipitation with 28% as compared with 21% in CMIP6 for MAM precipitation. Other indices highlight the biases of 8.1% (1.0%) for R95p, SDII (−3.9%) (−4.2), and R20mm (−0.8 days) (−1.0 days) while OND depicts biases of 29.8% (21.6%) for R95p, SDII (−2.2%) (−2.3), and R20mm (0.6 days) (0.1 days). This suggests that while the CMIP6 models simulated large biases in PRCPTOT and R95p, the models outperformed the CMIP5 models with lesser negative biases in SDII, R20mm, and CDD. Remarkably, most CMIP6 models are unable to simulate the extremely wet days (R95p) while satisfactory simulation of CDD is noted in CMIP6 over the study region. The model ensemble for the MAM season demonstrates a dry bias for most indices except for CDD over the study area while OND season shows wet bias for some indices (i.e., R95p, PRCPTOT), except for SDII, CDD, and R20mm.

3. A few CMIP6 models (e.g., NorESM2-MM, and CNRM-CM6-1) illustrate robust performance in reproducing the observed indices across all analyses. The majority of the CMIP6 models are still showing persistent biases. Consistent with other studies, the performance of the mean ensemble for both CMIP5/6 shows better performance due to the cancellation of some systematic errors in the individual models. Generally, CMIP6 shows improved performance in the simulation of the MAM season compared to CMIP5 models. Moreover, simulation of extreme indices is well captured in CMIP6 models relative to their predecessors. Generally, little improvement is noted over the East Africa domain in the new model generation despite the improved parametrization schemes, enhanced spatial resolution, and physical processes including the biogeochemical cycles (Eyring et al., 2016).
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CONFLICT OF INTEREST

The authors declare no conflicts of interest. All authors are in agreement with the content of the research.

AUTHOR CONTRIBUTIONS

Huanhuan Zhu: Data curation; methodology; software; visualization. Hamida Ngoma: Formal analysis; resources; writing-review & editing. Hassan Babaousmail: Methodology; software; visualization. Rizwan Karim: Writing-review & editing. Victor Dike: Formal analysis; validation; writing-review & editing.

ORCID

Brian Ayugi https://orcid.org/0000-0003-3660-7755

Hamida Ngoma https://orcid.org/0000-0002-3690-244X

Hassan Babaousmail https://orcid.org/0000-0001-6648-574X

Karim Rizwan https://orcid.org/0000-0001-9451-6080

Victor Dike https://orcid.org/0000-0003-2268-5859

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