



Performance evaluation of CMIP6 in simulating extreme precipitation in Madagascar

Mirindra Finaritra Rabezanahary Tanteliniaina^{1,2} · Jun Zhai^{2,3} · Mihasina Harinaivo Andrianarimanana⁴

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Abstract

This study assesses the performance of 37 global climate models (GCMs) from the Coupled Model Inter-comparison Project Phase 6 (CMIP6) in simulating extreme precipitation in Madagascar. In this study, six extreme precipitation indices from the Expert Team on Climate Change Detection and Indices (ETCCDI) were used, namely consecutive dry days (CDD), heavy precipitation days (R10MM), very heavy precipitation days (R20MM), maximum 5-day precipitation (RX5DAY), extremely wet days (R99P), and simple daily intensity (SDII). The performance of the model was evaluated from 1998 to 2014 against the Tropical Rainfall Measuring Mission 3B42 (TRMM) and the Global Precipitation Climatology Project (GPCP). The results show that most of the models in CMIP6 reasonably reproduce the annual precipitation cycle of the study area. The results also suggested that models from CMIP6 tend to underestimate extreme precipitation indices such as CDD, R20MM, SDII, and R99P. However, for R10MM and RX5DAY, the performance of individual models varies remarkably. By looking at the performance metrics, not a single model consistently performed well. Model performance changes with the reference data, the extreme precipitation indices, and the performance metrics. However, the findings of this study indicate that overall, multi-model ensemble mean outperforms most individual models. The study lays the basis for the analysis and projection of future extreme precipitation in Madagascar but also provides scientific evidence for the choice of models.

1 Introduction

Precipitation has an important role in the development of low- and lower-middle-income countries whose economies highly depend on agriculture. For instance, statistics from the World Bank showed that, in 2022, value added from agriculture, forestry, and fishery activities accounted for 20.23% of their Gross Domestic Products (GDP; <https://data.worldbank.org/>). However, in these countries, agriculture is a rainfed activity subject to high climate risks (Rama

Rao et al. 2022), making productivity uncertain. Hence, the variability in rainfall coupled with the increase in extreme precipitation events observed and reported globally (Gimeno et al. 2022; Mukherjee et al. 2018; Tabari 2020) constitute a threat to these already vulnerable countries.

The understanding of the earth's climate system strongly depends on the accuracy of information provided by global climate models (GCMs) from the Coupled Model Inter-comparison Project (CMIP). Thus, many disciplines, such as agriculture and hydrology, significantly rely on their accuracy. Yet, compared with observations, GCMs have been stated to display significant systematic bias. Therefore, the latest version (CMIP6) was reportedly developed to overcome the inconsistencies and bias of previous versions (i.e., CMIP3 and CMIP5), especially regarding the simulation of precipitation at a local scale (Eyring et al. 2016; Randriatsara et al. 2022). Since the release of CMIP6, it has been used in the simulation and projection of future precipitation by several studies (Almazroui et al. 2020; Majdi et al. 2022; Moradian et al. 2023; Xin et al. 2020).

Over the past few years, several studies have investigated the performance of CMIP6 in simulating precipitation extremes. Among these, the study of Chen et al. (2021)

✉ Mirindra Finaritra Rabezanahary Tanteliniaina
mirindra@qq.com

¹ College of Civil Engineering, Chongqing University, Chongqing 400045, China

² Institute for Smart City of Chongqing University in Liyang, Chongqing University, Liyang 213300, Jiangsu, China

³ College of Environment and Ecology, Department of Water Science and Engineering, Chongqing University, Chongqing 400045, China

⁴ Management Science and Engineering Post-Doctoral Research Station, China Three Gorges University, Yichang 443002, China

conducted in the Western North Pacific reported a significant improvement in CMIP6 models but was limited to the wet season. A study conducted in East Africa shows that CMIP6 models overestimate total wet-day precipitation and consecutive wet days but underestimate very wet days and maximum 5-day precipitation (Akinsanola et al. 2021; Ayugi et al. 2021; Faye & Akinsanola 2022). Compared with its predecessor, which tends to overestimate extreme climates (Alexander & Arblaster 2017), models from CMIP6 were reported to show substantial improvement in simulating indices that reflect precipitation intensity and frequency (Ayugi et al. 2021; Kim et al. 2016). However, previous studies also reported an underestimation of precipitation extremes by the latest CMIP, especially at the regional and local scales (Akinsanola et al. 2021; Ayugi et al. 2021; Chen et al. 2021; Faye & Akinsanola 2022). In addition, models from CMIP6 have varying results in the simulation of extreme precipitation. Yet, to this date, limited studies examined the performance of individual models from CMIP6 in simulating extreme precipitation at local scale.

This paper brings particular attention to Madagascar, an island home to a hyper-diverse biota with an incomparable level of endemism (Antonelli et al. 2022; Culbertson et al. 2022; Ralimanana et al. 2022). Madagascar is also a country where extreme events such as droughts and floods are frequent and devastating (Rabezanahary Tanteliniaina & Andrianarimanana 2023; Randriamarolaza et al. 2022; Randriamparany & Randrianalijaona 2022). A previous study reported that climate extremes in Madagascar are rarely studied (Stouffer et al. 2017). Importantly, it is one of the most complex regions where CMIP GCMs face challenges in simulating extreme precipitation (Lim Kam Sian et al. 2021). Nevertheless, it has been reported that over the last decades, Madagascar has shown a trend towards drier conditions (Randriamarolaza et al. 2022). Based on CMIP6 models, this drying trend over the Southeast African region is projected to continue in the future (Lim Kam Sian et al. 2022). In addition, Madagascar is particularly vulnerable to the impact of climate change and global warming. An increase of about 1.5 °C in global temperature leads to a rise in extreme rainfall in Madagascar (Barimalala et al. 2021). Although there are already few studies investigating past and future extreme precipitation in Madagascar using models from CMIP6 (Ayugi et al. 2022; Lim Kam Sian et al. 2021), a study that specifically investigates the performance of CMIP6 models in Madagascar is still inexistent. Therefore, assessing the ability of CMIP6 to simulate precipitation extremes over Madagascar is of great significance, not only for model developers and the climate modeling community but also for policymakers who rely on the accuracy of the results from climate models to develop policies and strategies to mitigate and adapt to climate change. Evaluating

the performance of CMIP6 models in simulating extreme precipitation at a local scale helps improve model components and parameterizations which will eventually lead to more reliable and accurate climate projections (Akinsanola et al. 2021). In addition, it increases confidence in the ability of models to accurately simulate local climate conditions. Evaluating the performance of CMIP6 models at the local scale provides valuable information for downscaling efforts, helping to refine climate projections for specific regions.

This study intends to close the existing gap in the literature regarding the choice of GCMs when studying future extreme precipitation at a local scale. For that, 37 GCMs from the CMIP6 were assessed against two gridded observed daily precipitation, namely the Global Precipitation Climatology Project (GPCP, Huffman et al. 2001) and the Tropical Rainfall Measuring Mission 3B42 (TRMM) version 7 (Huffman et al. 2007, 2010). In this study, six extreme precipitation indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) were used. More specifically, this study aims to investigate the performance of models from CMIP6 in simulating extreme precipitation indices in Madagascar. The specific questions addressed in this study are the following: (1) how well do CMIP6 GCMs simulate extreme precipitation at a local scale? and (2) are there extreme precipitation indices that are more challenging to simulate than the others? The remainder of this paper is organized as follows. The next section, i.e., Section 2, gives a detailed description of the study area, the data, and the methods used in this study. Section 3 describes the results, and Section 4 discusses the results and describes the limitations of this study. The last part of this paper is the concluding remarks, highlighting the main findings from this study.

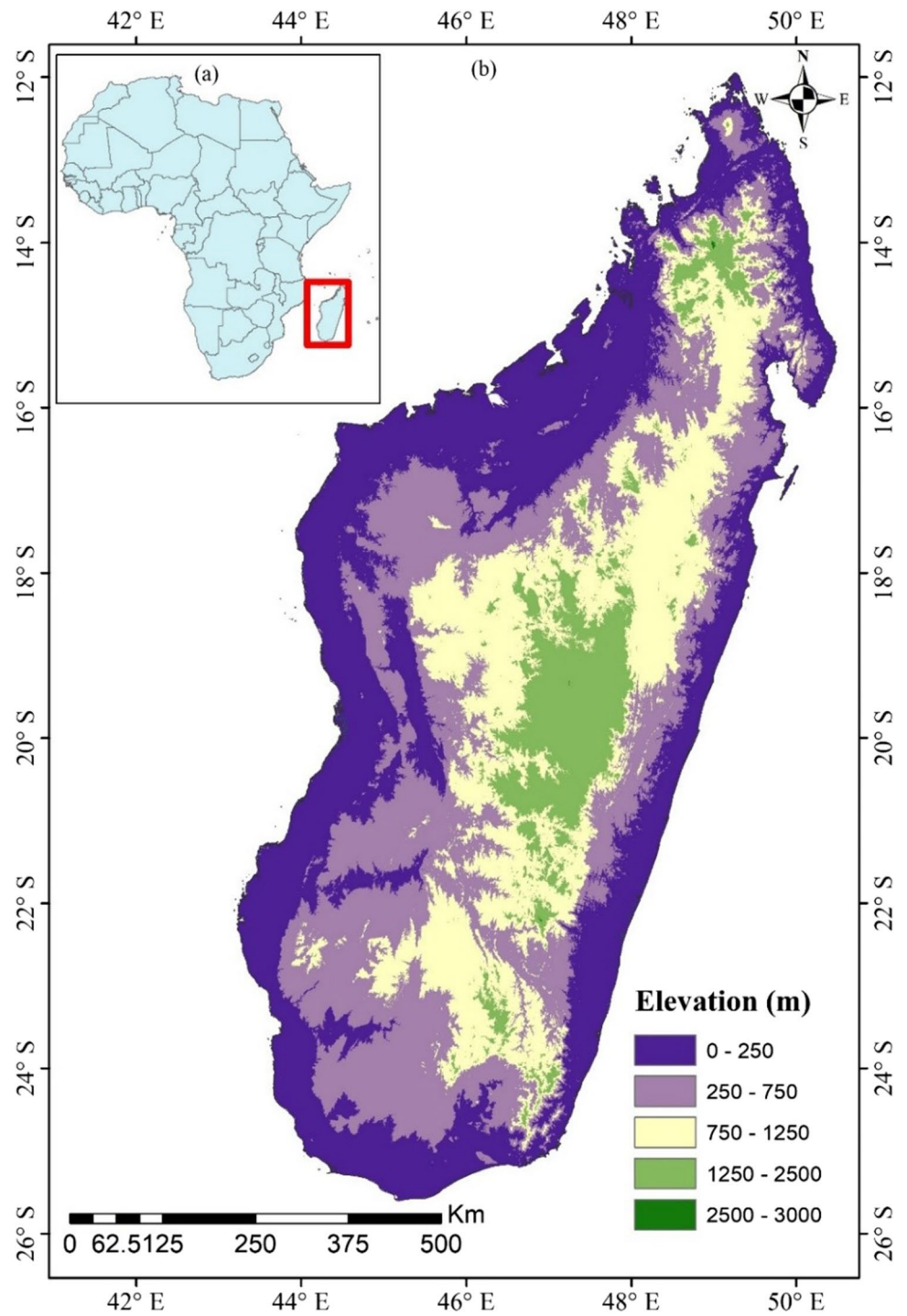
2 Method

2.1 Study area

Madagascar, the fourth largest island in the world ($\approx 590,000 \text{ km}^2$), is located in the Indian Ocean just off the edge of the southeast coast of the African continent, between $12^\circ\text{--}26^\circ\text{S}$ and $42^\circ\text{--}51^\circ\text{E}$ (Fig. 1). In terms of annual precipitation, Madagascar experiences a significant spatial variability. The east coast is wet, whereas the west and southwest coast is generally drier. It is a country known to suffer particularly from climatic hazards. For instance, the great South of Madagascar is known as a region where famine and food crisis, especially the one from July 2019 to June 2021, is linked to low precipitation and droughts (Harrington et al. 2022; Puri & Puri 2022; Ralaingita et al. 2022).

Madagascar has two distinct seasons, which are the rainy and humid summer from November to April and the dry and

Fig. 1 Location of the study area; **(a)** Geographic location of Madagascar in the African continent, **(b)** Topographic map of Madagascar



cold winter from May to October (Randriamarolaza et al. 2022; Randriatsara et al. 2022; Tanteliniana et al. 2020). The island has five types of climates according to the annual precipitation: the tropical rainforest climate (more than 2000 mm per year), the tropical monsoon climate (1500 to 2000 mm per year), the tropical savanna climate (1000 to 1500 mm per year), the semi-arid climate (600 to 1000 mm per year), and

the arid climate (less than 600 mm per year) (Tanteliniana et al. 2020). The average temperature also varies between the regions. It ranges between 14 and 22 °C in the central highlands and 23 to 27 °C in the coastal area (Randriamarolaza et al. 2022). The country is reported to be highly vulnerable to the impact of climate change (Nematchoua et al. 2018). Yet, it is often overlooked by the global literature.

2.2 Data and method

This study assesses the performance of CMIP6 models and their ensemble mean (Ens_mean), a simple arithmetic mean of the individual models (Eyring et al. 2016), in simulating extreme precipitation. More specifically, the performance of CMIP6 models was evaluated against the data from the Global Precipitation Climatology Project (GPCP; Huffman et al. 2001) and the Tropical Rainfall Measuring Mission 3B42 (TRMM) version 7 (Huffman et al. 2007, 2010), for the period from 1998 to 2014. It is worth noting that a relatively short period of analysis does not affect the reliability and validity of the evaluation (Chen et al. 2021). The GPCP and TRMM have been successfully used by previous studies with relatively similar scope to the present research (Akinsanola et al. 2021; Chen et al. 2021). The historical daily precipitation from 37 CMIP6 models was downloaded from the Earth System Grid Federation's website. The list of the CMIP6 models assessed in this study is provided in the supplementary information Table S.1. The choice of the 37 climate models was based on the availability at the time of the analysis because this study only used the first realization 'r1i1p1f1'.

The climate models, the GPCP, and the TRMM have different spatial resolutions (see Table S.1 for the spatial resolution of individual climate models). The GPCP data has a spatial resolution of $1^\circ \times 1^\circ$ while the TRMM has a spatial resolution of $0.25^\circ \times 0.25^\circ$. Therefore, before the analysis, the simulated and observed data were re-gridded to a common spatial resolution of $1^\circ \times 1^\circ$ using the bilinear remapping technique.

2.3 Extreme precipitation indices

This study used six extreme precipitation indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI) as listed in Table 1. These non-parametric indices were calculated using the daily precipitation. They have been used by previous studies to

measure the performance of climate models in reproducing extreme precipitation in other African regions (Akinsanola et al. 2021; Ayugi et al. 2021; Faye & Akinsanola 2022; Ongoma et al. 2018) and other regions around the world (Chen et al. 2021; Jeferson de Medeiros et al. 2022; Kim et al. 2020; Srivastava et al. 2020). It is also worth mentioning that the analysis in this study focuses on the wet season, i.e., from November to April (NDJFMA season).

2.4 Evaluation metrics

Following the method used in Akinsanola et al. (2021); and Faye & Akinsanola, (2022), three different evaluation metrics, namely Normalized Root Squared Mean Error (NRMSE), the percentage of bias (PBIAS), and the Pattern Correlation Score (PCC), were used to assess the performance of CMIP6 models in simulating extreme precipitation. By using various extreme precipitation indices and metrics, the methodology used in this study allows for an in-depth evaluation of the performance of CMIP6 models (Akinsanola et al. 2021; Sillmann et al. 2013).

$$\text{NRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - O_i)^2}}{\frac{1}{n} \sum_{i=1}^n O_i} \quad (1)$$

$$\text{PBIAS} = \frac{\sum_{i=1}^n (M_i - O_i)}{\sum_{i=1}^n O_i} \quad (2)$$

$$\text{PCC}(M,O) = \frac{\text{Cov}(M,O)}{\sqrt{\text{Var}(M)\text{Var}(O)}} \quad (3)$$

where Cov is the covariance, Var is the variance, n represents the total number of observations, and M_i and O_i denote the model and observed data, respectively.

Table 1 List of the extreme precipitation indices used in the present study based on ETCCDI

Extreme indices	Full name	Description	Units
SDII	Simple daily intensity	Annual total precipitation divided by the number of wet days	mm/day
CDD	Consecutive dry days	Annual maximum number of consecutive dry days (i.e., daily precipitation less than 1 mm)	days
RX5day	Maximum 5-day precipitation	Annual maximum of 5 days of precipitation amount	mm
R10mm	Heavy precipitation days	Annual number of days with precipitation more than 10 mm	days
R20mm	Very heavy precipitation days	Annual number of days with precipitation more than 20 mm	days
R99pTOT	Extremely wet days	The 99th percentile of precipitation intensity on wet days in the analyzed period	mm

3 Results

3.1 Climatology

The monthly precipitation over Madagascar based on the CMIP6 models and the two observed data, TRMM and GPCP, is reported in Fig. 2. The results support the findings from previous research and indicate that the wet season in Madagascar starts in November and ends in April, with January as the wettest month, while the dry season begins in May and ends in October, with August as the driest month. Precipitation from GPCP and TRMM displays little difference (the *p*-value from the Kruskal–Wallis test is higher than 0.05, thus the difference between the samples is not statistically significant). According to GPCP, the average monthly rainfall in Madagascar ranges from 19.69 mm/month to 342.78 mm/

month. Referring to TRMM, the average monthly rainfall in Madagascar is between 19.24 mm/month and 332.79 mm/month. In addition, most CMIP6 models overestimate precipitation, especially during the dry months (MJJASO). A comparative analysis between the precipitation from the models and the reference data shows no significant difference. However, it is worth noting that IITM-ESM and CESM2 display low precipitation rates during the peak in January, with only 135.84 mm/month and 153.80 mm/month, respectively. BCC-ESM1 also shows the lowest precipitation rate during the dry month, with only 9.64 mm/month in August. On the contrary, INM-CM5-0 exhibits the highest precipitation peak in January, with 412.48 mm/month. Overall, the 37 models and Ens_mean fairly reproduced the annual precipitation cycle over Madagascar, suggesting a better reproducibility of annual rainfall in Madagascar by the new CMIP6. In line

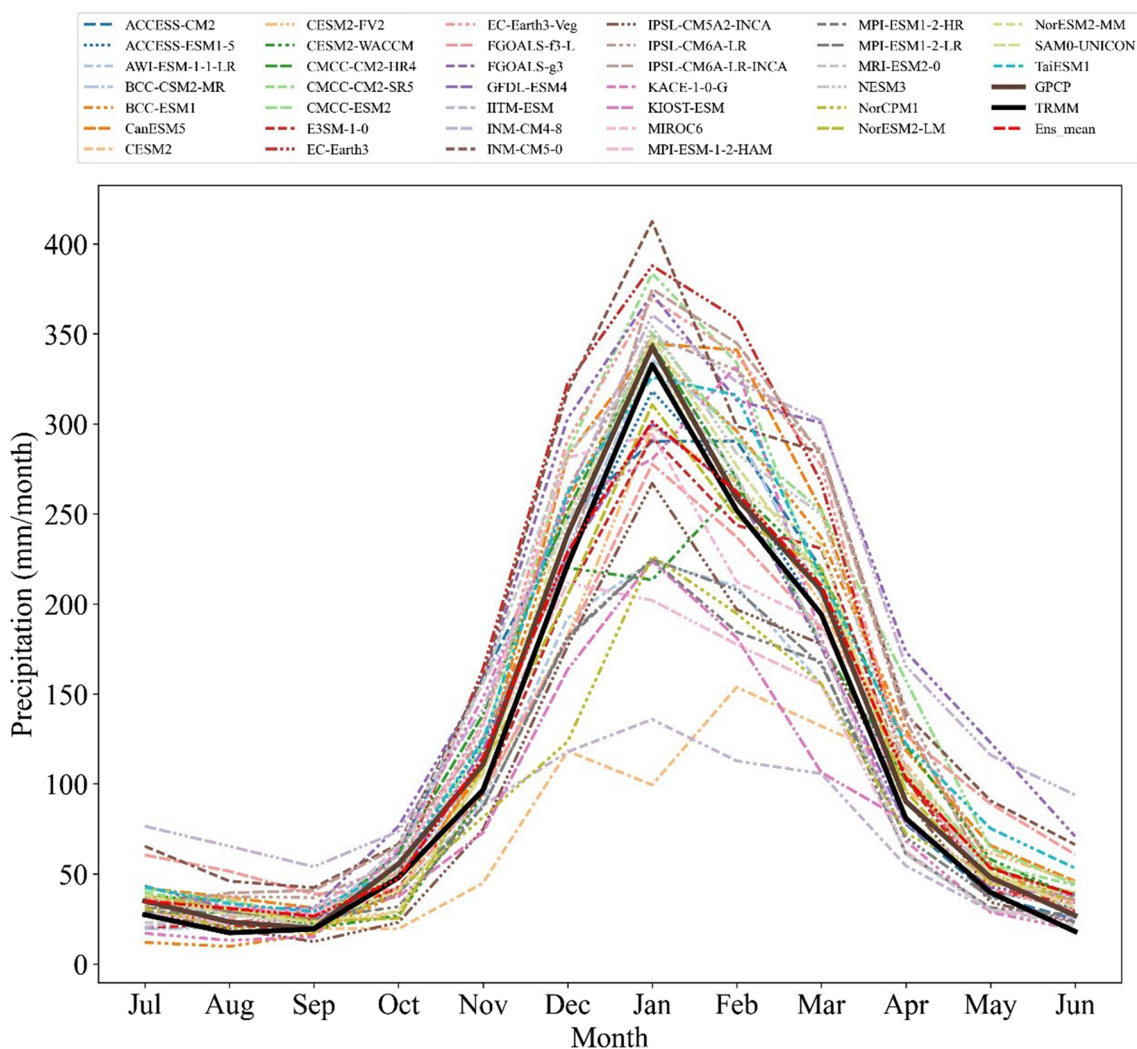


Fig. 2 Annual cycle of precipitation from the 37 CMIP6 models, TRMM (black solid line), GPCP (brown solid line) and multi-model ensemble during 1998–2014 over the study area

with previous research, this indicates that CMIP6 models and their ensemble mean show better performance (Ayugi et al. 2021; Zamani et al. 2020).

3.2 Spatial analyses of precipitation extremes

The difference between the spatial distribution of the six extreme precipitation indices from individual CMIP6 models and the reference data is shown in Figure S1 to Figure S12 in the supplementary information. Figure 3 displays the spatial distribution of the extreme precipitation indices

from the Ens_mean, TRMM, and GPCP. According to Fig. 3, the results from Ens_mean relatively agree with the spatial distribution of the extreme precipitation indices from TRMM and GPCP. It should be noted that the magnitude of the extreme precipitation indices from the Ens_mean is closer to GPCP than to TRMM, which is also the case for the precipitation extremes in West and East Africa (Akinanola et al. 2021; Faye & Akinanola 2022). Overall, the results show that the Ens-mean tends to slightly underestimate the extreme precipitation in Madagascar (Figure S1 to Figure S12).

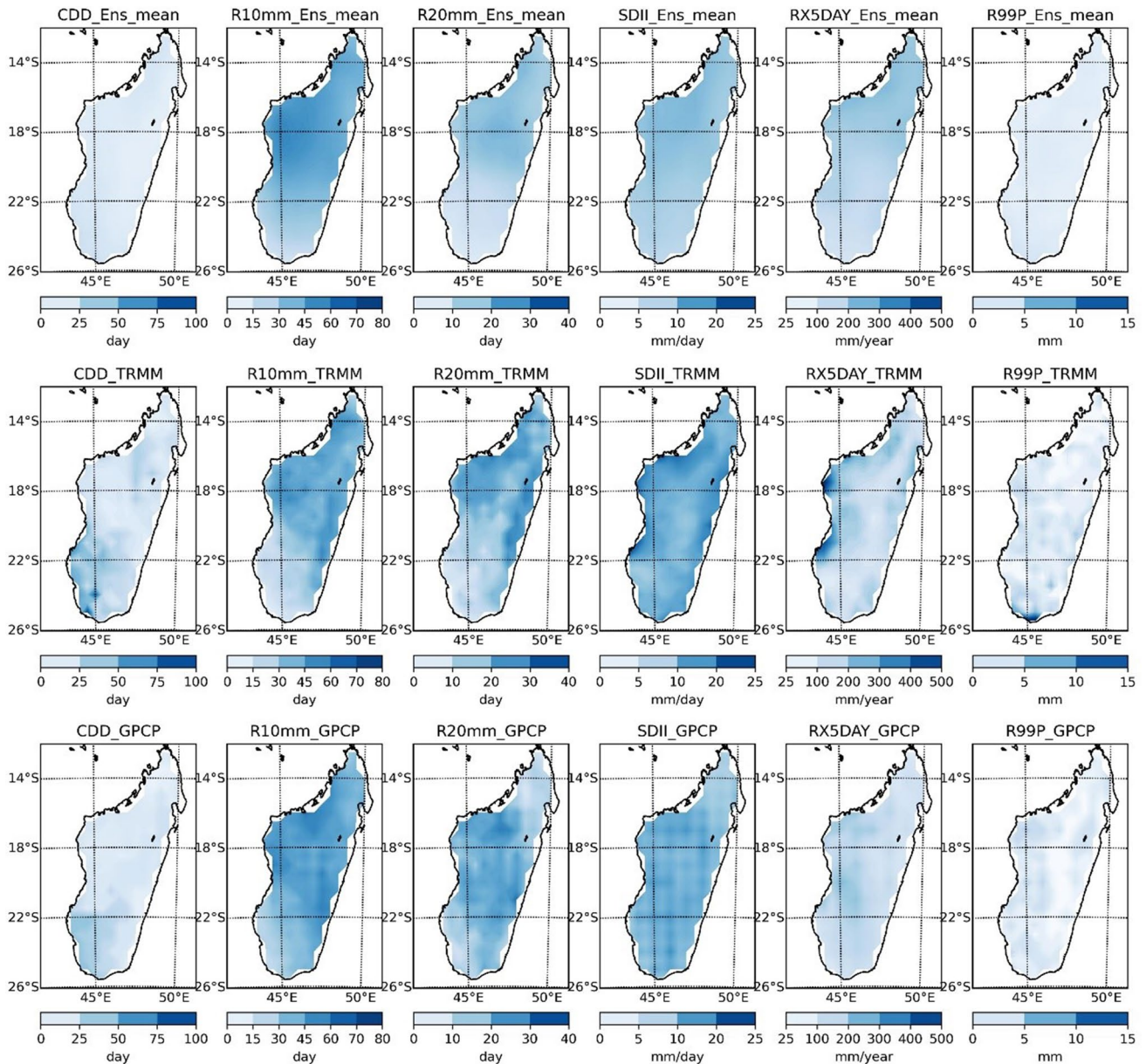


Fig. 3 Spatial distribution for the NDJFMA season of the CDD, the R10mm, R20mm, SDII, R99P, and RX5DAY (from left to right) in Madagascar, for the period of 1998 to 2014. Maps in the first row

show the ensemble mean, those in the second row are the TRMM, and maps in the last row are from the GPCP

The results indicate that against the two reference data, the majority of CMIP6 models underestimate the CDD (Figure S1 and S2) for the entire country, while some models slightly overestimate CDD (e.g., AWI-ESM-1-1-LR, CESM2, FGOALS-f3-L, NorCMP1, NorESM-LM) in the West and North parts of the study area. Only IIT-ESM exhibits a noticeable positive bias in the South. This overall underestimation of CDD is consistent within the African region as reported by previous research (Ayugi et al. 2021; Ogega et al. 2020). Regarding R10MM (Figure S3 and S4), the results from individual models show significant spatial heterogeneity. Models like CESM2, IIT-ESM, and KIOST-ESM show large underestimation (> -35 days) of R10MM over the whole country, while models like IPSL-CM6-LR and IPSL-CM6A-LR-INCA exhibit significant overestimation ($> +40$ days), especially in the central highlands. This result is similar to the findings of Faye & Akinsanola, (2022) in West Africa, which suggests that CMIP6 models overestimate the R10MM in the mountain regions (central highland in Madagascar). In terms of R20MM (Figure S4 and S5), SDII (Figure S7 and S8), and R99P (Figure S11 and S12) apart from FGOALS-f3-L with a noticeable overestimation of R20MM and R99P in the southwest part, the CMIP6 models underestimate these 3 extreme precipitation indices over the entire study area. In terms of RX5day (Figure S9 and S10) in particular, individual models show noticeable spatial disagreement. Models like AWI-ESM1-1-LR, CESM2, IIT-ESM, IPSL-CM5A2-INCA, IPSL-CM5A-LR, MPI-ESM-1-1-HAM, MPI-ESM1-2-HR, and MPI-ESM1-2-LR present negative bias for the entire country. On the other hand, models like BCC-CSM2-HR, BCC-ESM1, FGOALS-f3-L, and FGOALS-g3 show a large positive bias (more than $+175$ mm) mainly in the central highlands and northern part of Madagascar. Moreover, the results indicate that some models have spatial distribution similarity because they were developed by the same institution (e.g., models from the Max Planck Institute for Meteorology) (Akinsanola et al. 2021).

Overall, the results of this paper are in line with previous studies conducted in the African continent. For instance, Ayugi et al. (2021) conducted research in East Africa and found that GCMs from CMIP6 tend to underestimate CDD and R20MM. According to Chen et al. (2020), the prominent underestimation of CDD with GCMs can be attributed to the increased resolution of CMIP6, which leads to more precipitation that is often simulated at a much finer scale by high-resolution models.

3.3 Model performance

The capability of the CMIP6 models to realistically simulate extreme precipitation indices during the wet season in Madagascar is further assessed using metrics, namely

PBIAS, NRMSE, and PCC, as displayed in the portrait diagram in Fig. 4 and Fig. 5. Although the results discussed in this part focus on the average metrics for the entire study area, the spatial distribution of PBIAS and NRMSE is provided in the supplementary information (Figure S13 to Figure S24). A portrait diagram is a valuable tool used to individually assess the performance of models (Akinsanola et al. 2020). According to Fig. 4a and Fig. 5a, most CMIP6 models underestimate (blue color) CDD, R20MM, SDII, and R99P with $PBIAS < 0$. For CDD, only CESM2 exhibits a positive bias of 38.76% and 58.00% relative to TRMM and GPCP, respectively. For CDD against TRMM, the model with the lowest PBIAS is IITM-ESM with $PBIAS -2.79\%$, and relative to GPCP, the best performing model for CDD is MPI-ESM1-2-LR with a $PBIAS$ of -0.61% . However, the largest PBIAS is attributed to INM-CM4-8. IITM-ESM has the largest negative bias for R20MM, SDII, and RX5DAY relative to TRMM and R10MM, R20MM, and SDII relative to GPCP. On the contrary, models like CESM-FV2, FGOALS-f3-L, CanESM5, ACCESS-ESM1-5, NESM3, and MRI-ESM2-0 exhibit low bias. Exceptionally, against TRMM, EC-Earth3 shows the largest bias for R10MM but also has the best performance in simulating SDII. This indicates that the performance of the model can contrast depending on the extreme precipitation indices. Looking at the PBIAS, despite not being the best-performing model, in terms of overall performance (i.e., considering all extreme precipitation indices), Ens_mean outperforms most of the individual models.

To complement the evaluation conducted using PBIAS, NRMSE was used as it is less influenced by spatially compensating errors (Akinsanola et al. 2021). NRMSE of the 37 models and their ensemble mean is displayed in Fig. 4b and Fig. 5b. In general, a lower NRMSE value (i.e., $NRMSE = 0$) indicates less residual variance for a model, which translates to better model performance. Consistent with previous studies (Akinsanola et al. 2021; Ayugi et al. 2021), results show that Ens_mean outperforms other models in the simulation of CDD, R10MM, RX5DAY, and R99P relative to both TRMM and GPCP, and in R20MM against TRMM. For the SDII in particular, EC-Earth3 shows a good model performance with a $NRMSE_{SDII}$ of 0.29 against TRMM and $NRMSE_{SDII}$ of 0.25 against GPCP. However, in line with the results from PBIAS, IITM-ESM has high NRMSE for R10MM, R20MM, and SDII. Other models like CESM2, BCC-CSM2-MR, and FGOALS-f3-L also have high NRMSE for CDD, RX5DAY, and R99P, respectively. Generally, the results show that most CMIP6 models have difficulty simulating R99P with an $NRMSE_{R99P}$ particularly high (more than 0.75).

The spatial correlation (PCC) is displayed in Error! Reference source not found. Fig. 4c and Fig. 5c. It shows that the PCC strongly varies according to the climate models.

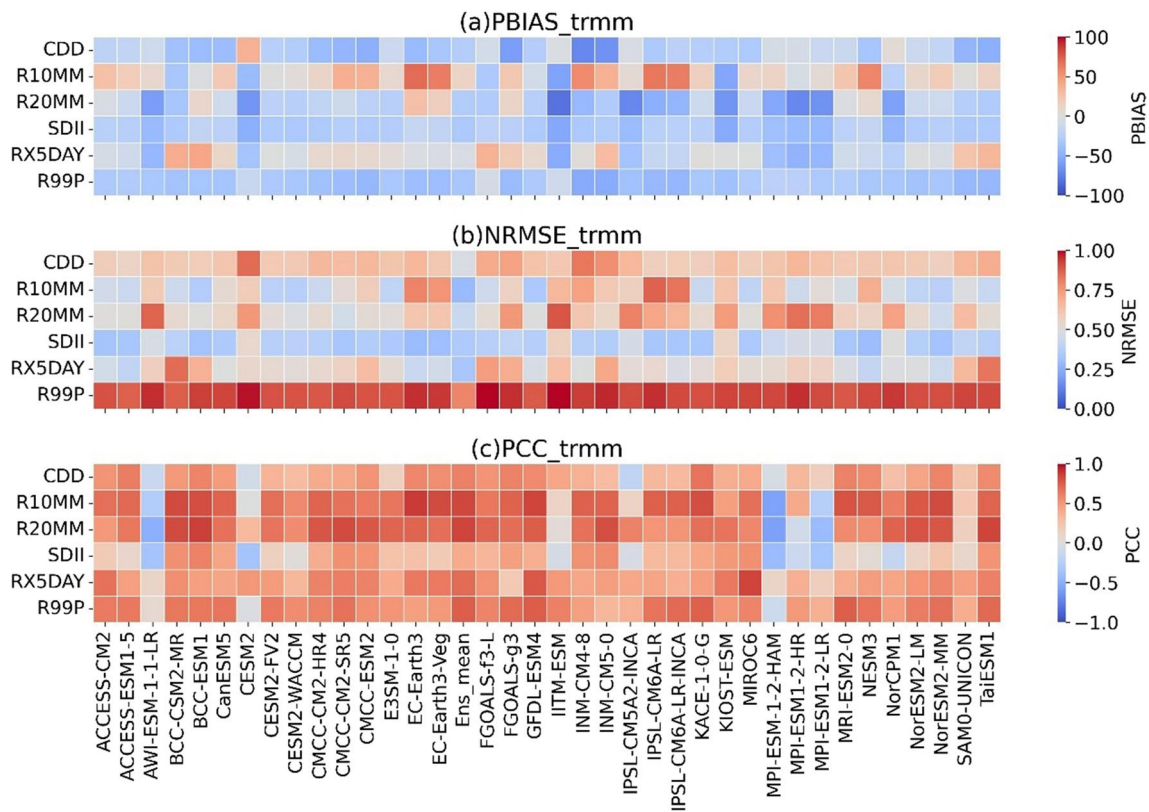


Fig. 4 Portrait diagram showing the PBIAS between the climate models and TRMM during 1998–2014

However, the results suggest that most CMIP6 models have relatively good values of PCC more than 0.5 for CDD, R10MM, R20MM, and R99P. In line with previous findings of Ayugi et al. (2021) conducted in East Africa, the results indicate that reproducing the spatial pattern of SDII and RX5DAY remains a challenge for models from CMIP6. Furthermore, the results show that CMIP6 models have a higher spatial correlation with TRMM than with GPCP. This indicates that although the magnitudes of extreme precipitation are closer to GPCP, the spatial patterns of extreme precipitation from CMIP6 models are more similar to TRMM. By focusing on the PCC against TRMM, the best PCC score is attributed to KACE-1-0-G (CDD), EC-Earth3 (R10MM), BCC-ESM1 (R20MM and SDII), MIROC6 (RX5DAY), GFDL-ESM4 (R99P). Against GPCP, the best PCC score is associated with ACCESS-ESM1-5 (CDD), CESM-WACCM (R20MM and SDII), CanESM5 (RX5DAY), and BCC-ESM1 (R99P). Similar to the two previous metrics, PCC shows that Ens_mean fairly reproduced the pattern of extreme precipitation from the two reference data and outperformed most of the individual models. This is due to the reduction of the systematic bias in individual models (Ayugi et al. 2021; Faye & Akinsanola 2022).

4 Discussion

This study conducted a performance evaluation of CMIP6 models in simulating extreme precipitation in Madagascar by focusing on the wet season (NDJFMA season). Therefore, six extreme precipitation indices calculated from CMIP6 models were compared against two gridded precipitation data (GPCP and TRMM) using PBIAS, NRMSE, and PCC.

The results showed that despite the improved parametrization, enhanced spatial resolution, and physical processes with the integration of the biogeochemical cycles in CMIP6 (Eyring et al. 2016), individual models still have persistent bias and have difficulty with the simulation of extreme precipitation at the local scale. In line with previous research, the results highlight the bias that CMIP6 models exhibit when simulating extreme precipitation in the tropics, arid, and semi-arid regions (Abelmoaty et al. 2021). This modest performance of most CMIP6 models can be associated with the model parametrization in complex regions like Madagascar. The mesoscale features at the local scale, such as topography, vegetation cover, or coastline cause important regional heterogeneity and affect the performance of individual

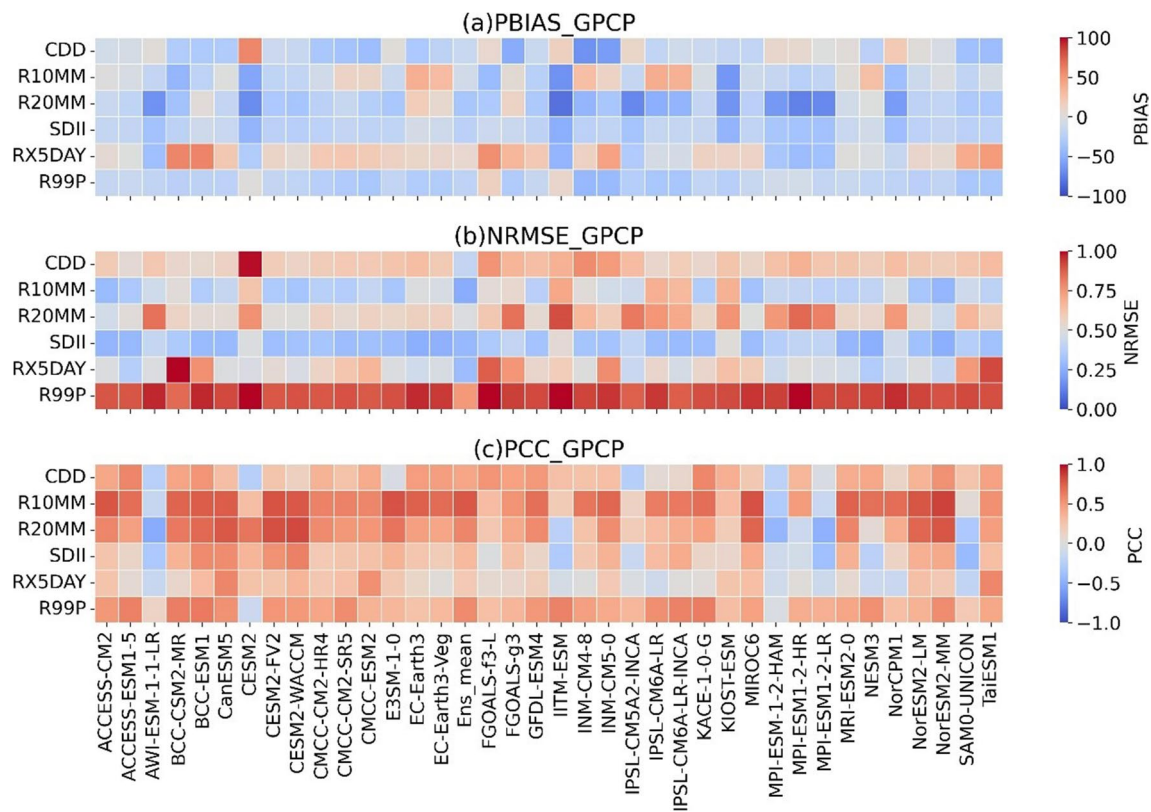


Fig. 5 Same as Fig. 4 but for GPCP

models (Nikulin et al. 2012). In particular, the topography was reported to significantly influence the ability of models to replicate local precipitation (Shiru & Chung 2021). In 2018, Rondrotiana Barimalala et al. (2018) suggested that a misrepresentation of the topography could contribute to the bias in precipitation in climate models over the southern Africa region. Moreover, the robust trade winds in the Indian Ocean also affect the ability of models to capture the air-sea interaction, hence affecting the accuracy of extreme precipitation simulation (Randriatsara et al. 2023).

Previous studies reported that as a result of the cancellation of systematic errors in the individual models, ensemble mean performance should outperform individual models (Ayugi et al. 2021; Faye & Akinsanola 2022). Similar to the findings of previous study, the results show that overall, the multi-model mean has better performance compared to most of the individual models. Nevertheless, based on the overall performance, not one model stands out as the best for Madagascar in the simulation of extreme precipitation which is also the case for Brazil (Jeferson de Medeiros et al. 2022). This enhances the necessity of using a multi-model mean which reduces the systematic bias from individual models (Akinsanola & Zhou 2019). In addition, the overall performance of CMIP6 in simulating extreme precipitation

reported in this study calls for significant improvement of individual models in the representation of complex features at the local scale. The results of this study highlight the need to constantly improve CMIP6 performance, especially at smaller and regional scales.

The important impacts of extreme precipitation in Madagascar is worth mentioning. Extreme events endanger the endemic fauna and flora of Madagascar (Dunham et al. 2011). The literature has shown that extreme precipitation continuously threatens the biodiversity and environmental systems of the country (Randriamarolaza et al. 2022). The change in rainfall patterns induced a dietary shift of lemurs as a response to environmental stress and the alteration of Coral reef Communities in Southwest Madagascar (Carter et al. 2022). Besides the negative effect of extreme events on natural resources, precipitation variation has also severe effects on the socioeconomic life of the island. At the regional level, a study investigating the effect of tropical storms and cyclones showed that populations in Mozambique, Malawi, and Madagascar were extremely affected by floods. In addition, consecutive tropical storms increase the vulnerability of the population which fails to recover before another hits (Geris et al. 2022). Extreme precipitation also harms fishing activities by decreasing available fishing hours

thus, fish capture and income (Farquhar et al. 2022). Finally, precipitation extremes are expected to affect the hydrological system and hydropower generation (Obahoundje & Diedhiou 2022).

Although the results and findings from this study are relevant to the scientific community, the main limitation remains in the use of gridded reference data due to the lack of locally observed datasets. In addition, while the metrics used in this study are good indicators of model performance, according to Srivastava et al. (2020), given the models' complexity, using several metrics is advised. Nevertheless, this study is the first to study the performance of CMIP6 in simulating extreme precipitation in Madagascar, hence provides the basis for the analysis of future extreme precipitation in a tropical island like the study area. In addition, it offers scientific evidence for choosing appropriate GCMs for the projections of future climate extremes and gives the necessary information for model developers to identify subregions and processes. With the advancement of computing power, it is now possible to use the High-Resolution Model Inter-comparison Project (HighResMIP) for local study (Randriatsara et al. 2023). Therefore, future research are encouraged to conduct a comprehensive analysis of the performance of CMIP6 HighResMIP in the simulation of extreme events at a local scale.

5 Conclusions

This study evaluated the performance of 37 CMIP6 models against two gridded observation datasets, namely TRMM and GPCP in simulating extreme precipitation in Madagascar. Six extreme precipitation indices were chosen among the ones recommended by ETCCDI. The findings from this study can be summarized as follows:

- (1) CMIP6 models were able to fairly reproduce the annual climatology in Madagascar. IITM-ESM and CESM2 display low precipitation rates during the peak in January. BCC-ESM1 also exhibits the lowest precipitation rate during the dry month in August. On the contrary, INM-CM5-0 displays the highest rainfall peak in January. The precipitation from GPCP and TRMM are strongly similar.
- (2) Models from CMIP6 tend to underestimate extreme precipitation indices such as CDD, R20MM, SDII, and R99P. In addition, SDII and RX5DAY remain challenging for most of the models from CMIP6. Overall, because of the reduction of systematic bias, the performance of the Ens_mean outperforms most of the individual models. Therefore, policymakers are recommended to use a multi-model ensemble as the basis for their analysis, policies, and strategies.

- (3) Based on the evaluation metrics, extreme precipitation indices used in this study, and the overall performance, not one model stands out as the best. More specifically, the model performance varies with the reference data, the extreme precipitation indices, and the performance metrics. Most CMIP6 models still have significant bias. Nevertheless, based on the evaluation metrics, satisfactorily performing GCMs include MPI-ESM1-LR and IIT-ESM for CDD, CanESM5 and CESM-FV2 for R10MM, NESM3 and NorESM2-MM for R20MM, EC-Earth3 for SDII, ACCESS-ESM1-5 and CESM-FV2 for RX5DAY, and CESM2 and FGOAL-f3-L for R99P.

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Author contribution All authors contributed to the study conception and design. Conceptualization, data collection and analysis, formal analysis, data curation, and writing of original draft were performed by Mirindra Finaritra Rabezanahary Tanteliniaina. Supervision and Conceptualization were performed by Zhai Jun. Writing, review and editing were performed by Mihasina Harinaivo Andrianarimanana. All authors read and approved the final manuscript.

Data availability The datasets used in the current study are available at the Earth System Grid Federation (ESGF) at <https://esgf-node.llnl.gov/search/cmip6/>. Tropical Rainfall Measuring Mission 3B42 (TRMM) can be accessed at <https://rb.gy/agn5mh> and Global Precipitation Climatology Project is available at <https://rb.gy/uvr2vx>.

Declarations

Competing interest The authors declare no competing interests.

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