



Evaluation of the CMIP6 models in simulating climatic variables in the Cantareira Water Production System

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ABSTRACT

The Cantareira Water Production System is highly susceptible to the effects of climate changes. Extreme drought events affect reservoir levels and the water supply of millions of people. Therefore, water resource managers need reliable information about the of these events. Understanding the ability of global climate models to simulate climatic variables is essential to obtain reliable forecasts. In this context, this work evaluates the performance of 10 models from the recent Coupled Model Intercomparison Project Phase 6 (CMIP6) in simulating the main climatic variables for the Cantareira System area. For this, several statistical metrics (r , RMSE, Pbias and KGE) were used to evaluate the performance of each model in relation to the observed period (2000-2013) and combine the results to rank the top performances. The results show that the best ranked models were EC-EARTH3, INM-CM4_8, INM-CM5, ACCESS-ESM1-5 and MRI-ESM2, depending on the climate variable. Overall, the study highlights the importance of individual evaluation of MCGs and their appropriate selection to generate reliable information in climate studies.

KEYWORDS: CMIP6. Global Climate Models. Climate Change.

1 INTRODUCTION

Climate change has a significant impact on the hydrological system of basins. There is strong evidence that confirms the role of basins in modifying climatic variables, such as precipitation and temperature, as well as hydrological regimes observed in reservoirs around the world in recent decades (Gudmundsson *et al.*, 2021).

According to the latest reports from the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2022), the global climate has got warmer over the past few decades in all regions of the world, the average global surface temperature at the beginning of the twenty-first century was already 1.09°C higher than the average temperature at the beginning of the previous century (19th). The recorded increases in the concentration of greenhouse gases (GHG) since 1750 are unequivocally caused by human activities (Dong *et al.*, 2016; Dong; Sutton; Shaffrey, 2017; King *et al.*, 2016).

In the last years, climate change has caused a series of environmental impacts that manifest in adverse climate conditions, such as the increase in the frequency and intensity of extreme climate events, like droughts and intense rainfall (Siebers; Paillex; Robinson, 2019; Gudmundsson *et al.*, 2021).

As the name suggests, a drought is a period of abnormally dry weather that persists long enough to cause hydrological imbalances (Cook; Mankin; Anchukaitis, 2018). Most droughts begin with a persistent deficit in precipitation (“meteorological drought”) that develops over time into deficits in river flow and soil moisture, which leads to a reduction in the water supply capacity (“hydrological drought”). In the context of climate change, in addition to the lack of rainfall, a warmer climate can lead to changes in evapotranspiration that are critical components of drought (Mcdowell; Allen, 2016; IPCC, 2022).

Recently, the state of São Paulo suffered two prolonged and severe droughts. The first, in the early 2000s, was responsible for a major energy crisis. As for the second, in 2013, the drought seriously affected the water supply of approximately 9 million people in the metropolitan region of São Paulo (RMSP) (Marengo *et al.*, 2010). At this time, the Cantareira System saw a 56% drop in its contribution to the water supply production, from 33 m³/s at the beginning of the crisis, to 14 m³/s in March of 2015 (Custódio, 2015).

The hydrological impacts of climate change tend to aggravate existing and future risks

associated with water resources management (Tiwari; Mishra, 2022). In this context, for governments to be able to plan public policies integrated with the need for adaptation to these impacts, it is important to have reliable future climate projections, as to develop efficient strategies to avoid further setbacks in terms of climate change (Berhanu *et al.*, 2023a).

The Global Climate Models (GCMs) and Regional Climate Models (RCMs) are essential tools to investigate the impacts of climate change on the water regime of basins, as well as the future occurrence of these extreme events. In addition to projections, they are also used to study historical and current climatology (Agyekum *et al.*, 2023).

Nonetheless, to use GCMs (or RCMs) in studies over a specific region and period, it is necessary to verify their ability to simulate the observed climate conditions. Generally, model performance evaluations are made for several climate variables, comparing observed historical periods with those of the models. Metrics that investigate average errors, bias, and correlation between data, are examples of statistical methods used in the evaluation process (Agyekum *et al.*, 2022; Akinsanola; Ongoma; Kooperman, 2021; Faye; Akinsanola, 2022).

The evaluation can be made for one or more variables, on a temporal or spatial scale (or both), this will reduce uncertainties associated with the models and errors in the analyses, in addition to providing reliable projections for the future, by using appropriate models chosen from the performance evaluation (IPCC, 2014).

Several research groups around the world have developed climate models. The Coupled Model Intercomparison Project (CMIP) has as objective to produce and analyze global climate models and better understand past, present and future climate change (Eyring *et al.*, 2016). The models produced in the last IPCC study cycle, such as the CMIP6, presented improvements in spatial resolution and in the representation of physical processes when compared to the previous CMIP5 models (Eyring *et al.*, 2016).

There are relatively few studies that have evaluated the performance of CMIP5 models in Brazil, or even the South America (Almagro *et al.*, 2020; Falco *et al.*, 2019; Llopart; Reboita; Rocha, 2020; Solman; Blázquez, 2019), and the results showed a good performance of multi-model ensembles in simulating climate variables, while individual analyses presented more biases, reinforcing the need for individual evaluation of the models.

Regarding the evaluation of the CMIP6 project models, literature is even scarcer (Correa *et al.*, 2022; Dias; Reboita, 2021). Despite the proven importance of evaluating the performance of different CMIP6 models, there are no studies at national level that carry out this evaluation in a relevant way for impact studies in the face of climate change, let alone for an important area in terms of water supply such as the Cantareira System, or even the state of São Paulo. In this sense, this research seeks to fill this gap in the literature by carrying out an evaluation of the CMIP6 Global Climate Models performance in simulating climate variables in the Cantareira System region.

This study evaluates the ability of CMIP6 models to represent local climatology before using them to analyze future climate projections, this is made as to support adaptation and mitigation strategies for impacts resulting from climate change. It also aims at selecting the best CMIP6 models that could be used in reliable climate forecasts for the Cantareira System region.

1.1 General Objective

The general objective of this research is to evaluate the performance of the Global Climate Models of the CMIP6 project in simulating the monthly averages of precipitation, relative humidity, solar radiation, wind speed and maximum and minimum temperature for the Cantareira System area.

1.1.1 Specific objectives

First: to obtain observed climate data and data from CMIP6 climate models for the historical period.

Second: evaluate the individual performance of CMIP6 models for each variable, using statistical analysis.

Third: rank the performance of climate models by combining all used metrics.

2 METHODOLOGY

The performance evaluation of the models was carried out for the following variables: precipitation, relative humidity, solar radiation, wind speed and temperature.

The evaluation methodology follows three steps: initially, by obtaining observed climate data from the historical period of 2000 to 2013, and data from CMIP6 climate models for the same period.

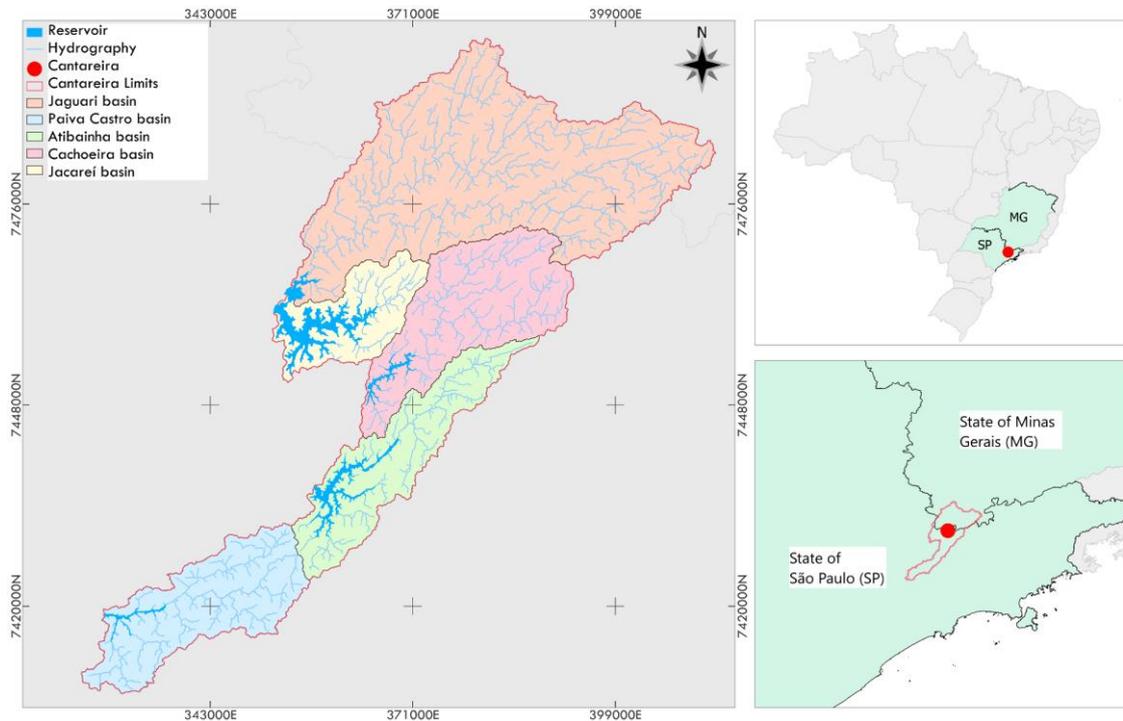
In the second stage, the individual performance of the CMIP6 models for each variable was evaluated by using statistical analysis. And finally, for the third stage, the performance of the climate models was ranked by combining all the used metrics.

2.1 Study Area

The Cantareira System (Figure 1) is located to the north of the Metropolitan Region of São Paulo (RMSP) and is one of the largest public supply systems in the world, with a water production that reaches 33 thousand liters per second, it is also responsible for supplying around 8.8 million people (46% of the population of the RMSP) (Whately; Cunha, 2006).

The Cantareira System is composed by: Five reservoirs (Jaguari, Jacareí, Cachoeira, Atibainha and Juquery), tunnels, and interconnecting channels between one dam and by another downstream, a water pumping station (Águas Claras) and a water treatment plant (ETA Guaraú). The water produced in the system comes from the five basins mentioned above, of which the largest is the Jaguari-Jacareí basin (interconnected reservoirs) (Gesualdo *et al.*, 2019; Whately; Cunha, 2006).

Figure 1 – Location of the Cantareira System



Source: the authors

2.2 Climatic data

2.2.1 Observed climatic data (period 2000-2013)

The observed climate data for precipitation (pr), relative humidity (hur), solar radiation (rss), wind speed (sfcwind) and temperature (tmax and tmin) used in this study were obtained from Xaxier et al. (2016), a dataset that contains daily data covering the entire Brazilian territory, in a grid with spatial resolution of $0.25^\circ \times 0.25^\circ$ (latitude/longitude).

The dataset developed by Xavier et al. (2016), as a result of quality control and the extensive network of rainfall (3625) and climate (735) stations used in its development, provides reliable information and has already been used and validated in several applications in the Brazilian territory (Dias; Martins; Martins, 2024; Silva *et al.*, 2023; Ferreira *et al.*, 2023; Marchezepe *et al.*, 2023).

2.2.2 CMIP6 Models

In order to obtain daily data from the climate models of the CMIP6 project, it was used the CLIMBra dataset (Ballarin *et al.*, 2023), which provides bias-corrected data from 10 CMIP6 models (table xx), also in a spatial resolution grid of $0.25^\circ \times 0.25^\circ$ (latitude/longitude), not only for future projections, but as well as for historical periods, as is the present case.

The dataset developed by Ballarin *et al.* (2023) is recent, however, it has also been used and validated in climate studies applied to the Brazilian territory (Ballarin *et al.*, 2023a; Ferreira *et al.*, 2023; Monteiro; Cabral, 2023; Reboita *et al.*, 2023).

Table 1 – List of MCGs used in the research.

Model	Institution	Country
ACCESS_ESM1	Australian Community Climate and Earth System Simulator Climate Model Version 1	Australia
CMCC_ESM2	Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy
EC_EARTH3	EC Earth Consortium	Europe
INM_CM4_8	Institute of Numerical Mathematics of the Russian Academy of Sciences	Russia
INM_CM5	Institute of Numerical Mathematics of the Russian Academy of Sciences	Russia
IPSL_CM6A	Institut Pierre Simon Laplace (IPSL)	France
MIROC6	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology (MIROC)	Japan
MPI_ESM1	Max Planck Institute for Meteorology (MPI-M)	Germany
MRI_ESM2	Meteorological Research Institute (MRI)	Japan
NorESM2	Norwegian Earth System Model	Norway

Source: the authors

2.3 Evaluation methods

2.3.1 Statistical metrics

The CMIP6 models were evaluated for their performance in simulating the climatology of the study area by comparing them with observed data on precipitation (pr), relative humidity (hur), solar radiation (rss), wind speed (sfcwind) and temperature (tmax and tmin).

The individual performance of the models was evaluated by using statistical methods, and the analysis was carried out considering the monthly averages. The statistical metrics used in this research include the correlation coefficient (r), the root mean square error (RMSE), the percentage bias (Pbias) and the Kling-Gupta efficiency coefficients (KGE). These metrics have been used in studies that sought to evaluate CMIP6 climate models in different regions of the planet (Agyekum *et al.*, 2022; Akinsanola; Ongoma; Kooperman, 2021; Berhanu *et al.*, 2023b; Faye; Akinsanola, 2022; Ignacio-Reardon; Luo, 2023; Yazdandoost *et al.*, 2021).

Table 2 – List of statistical metrics used in the research.

Statistical Metric	Equation	Amplitude	Best value
Bias percentage (Pbias)	$Pbias = \frac{\sum_{i=1}^n (Qobs - Qsim)^2}{\sum_{i=1}^n (Qobs)} \times 100$	$-\infty$ to $+\infty$	0
The Root Mean Square Error (RMSE)	$MSE = \sqrt{\frac{\sum_{i=1}^n (Qobs - Qsim)^2}{n}}$	0 to ∞	0
Pearson correlation coefficient (r)	$r = \frac{\sum_{i=1}^n (Qobs - Qmobs)^2 \times (Qsim - Qmsim)^2}{\sqrt{\sum_{i=1}^n (Qobs - Qmobs)^2 \times \sum_{i=1}^n (Qsim - Qmsim)^2}}$	-1 to 1	1
Kling-Gupta efficiency coefficients (KGE)	$KGE: 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$	$-\infty$ to 1	1

Source: the authors

2.3.2 Ranking of the MCGs

For each climate variable, the 10 CMIP6 models were ranked according to their performance regarding statistical metrics (r, RMSE, Pbias and KGE). The Composite Rating Index (CRI) was used to obtain the overall performance ranking of the CMIP6 models in the study area. A CRI value close to 1 indicates a good model performance, while values close to 0 indicate poor performance. The overall ranking (CRI) of Global Climate Models (GCMs) was calculated by using the following equation:

$$CRI = 1 - \frac{1}{nm} \sum_{i=1}^n rank_i$$

Where n and m represent the number of GCMs and indicators, respectively, and i represents the performance rank of the referred GCM for a given variable and metric. This approach of combining and ranking models has been successfully used in several studies (BERHANU et al., 2023; IQBAL et al., 2021; LI et al., 2022; SONG et al., 2023; TONG; ZHENG; FU, 2022).

RESULTS

3.1 Monthly averages of precipitation and temperature

When analyzing precipitation, maximum and minimum temperature data from CMIP6 climate models in comparison to the historical period of 2000 to 2013 (Figures 2-4), it is clear that, in general, the models capture the main seasonal trends. It is clearly visible the contrast

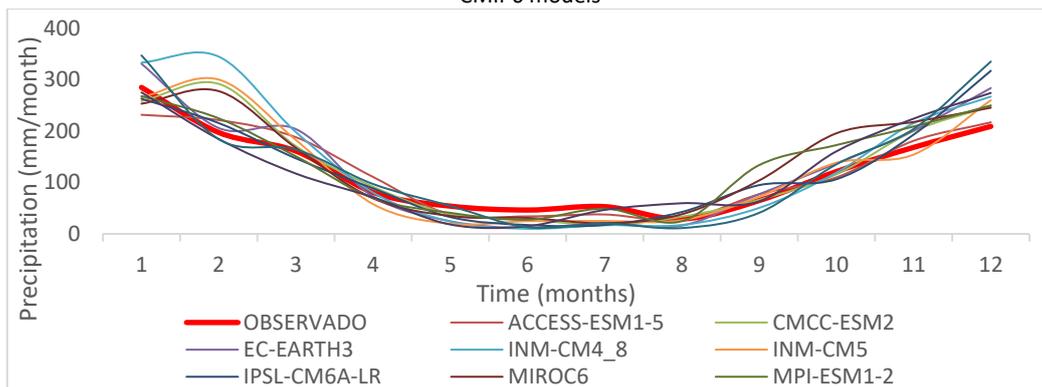
between the rainiest (Figure 2) and hottest (Figure 3 and 4) period, from October to April, and the driest and coldest period, between, approximately, the months of May and August.

For the precipitation patterns, the INM-CM4_8 was the model that presented the greatest discrepancy, estimating the highest monthly precipitation values, mainly in the months of December (334.96 mm) to February (344.56 mm). In the period between the months of April to August (drier), most models captured the observed values more accurately.

Regarding data on temperature, both for maximum (Figure 3) as for minimum values (Figure 4), the values simulated by the models show little discrepancy when compared to what is seen in precipitation patterns. For maximum temperature data, there is still some variability between the simulated and observed values, the NorESM2-MM, for example, reached a discrepancy of +1.2°C in February and -1.0°C in relation to the observed averages.

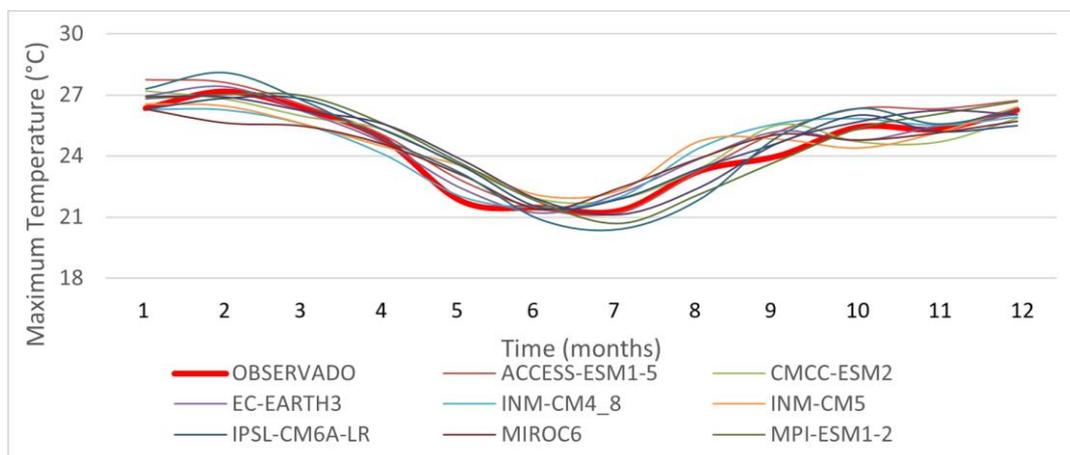
For the minimum temperature values, it is possible to observe that the models were more consistent in their performance, not presenting, a priori, large biases and average errors in most months of the year.

Figure 2 – Comparison between monthly precipitation averages from the observed historical period and data from CMIP6 models



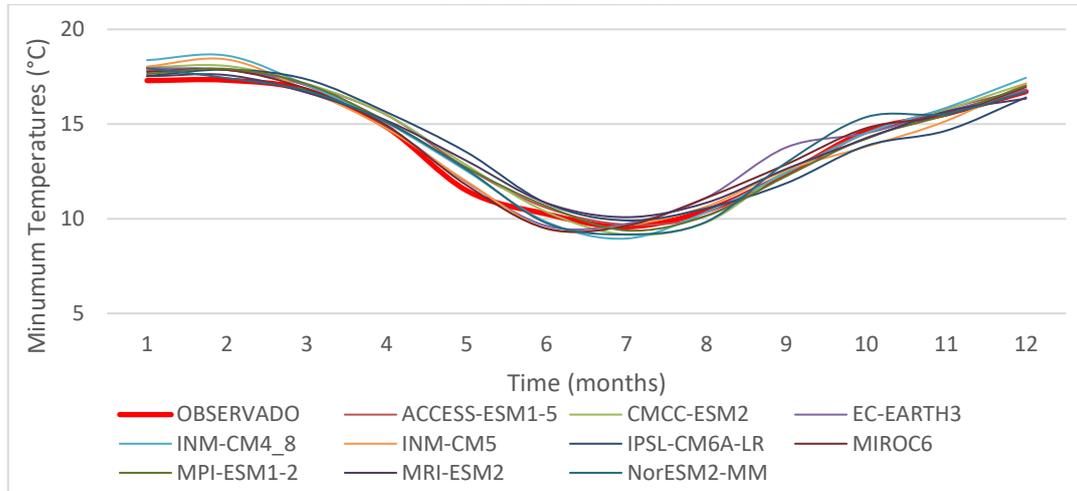
Source: the authors

Figure 3 – Comparison between monthly averages of maximum temperatures from the observed historical period and data from CMIP6 models



Source: the authors

Figure 4 – Comparison between monthly average minimum temperatures from the observed historical period and data from CMIP6 models.



Source: the authors

3.2 Statistical analysis of the MCGs

For precipitation (pr), it is noted a good correlation between the observed and simulated patterns, with 9 of the models (90%) presenting r above 0.65. On the other hand, some models presented large biases in the Pbias values, three (30%) of the models (INM-CM4_8, MPI-ESM1-2 and MPI-ESM2) had Pbias values above 10%. The RMSE showed considerable magnitude in relation to the average values of the observed data, the highest RMSE value is 3.19 for the INM-CM4_8 model, which is consistent with the graphical visualization of precipitation extremes (Figure 2). The KGE presented lower values in relation to the correlation coefficient, only two (20%) models (MIROC6 and MPI-ESM1-2) presented KGE above 0.60; this is due to the fact that the KGE does not consider only linear correlation, which had good values, but also the variability and bias of the data, and previously were found large discrepancies in these two aspects.

The values of relative humidity (hur) and wind speed (sfcwind) were those in which the models had the greatest difficulty in simulating the observed patterns. This is clearly seen in the correlation metrics and mean square errors. None of the models achieved r and KGE values greater than 0.60, and both variables and all models had mean errors of a high magnitude in relation to the observed averages.

For solar radiation values (rss), the models generally performed well. Eight (80%) of the models presented r values greater than 0.65 and KGE greater than 0.6. Biases and mean square errors were relatively small in relation to the observed means. The only ones that had a discrepant performance considering most metrics were the MIROC6 and the CMCC-ESM2.

Maximum temperature values had reasonable but consistent performance, having no models discrepant when compared to the others. Most models presented r and KGE values close to 0.6 and low bias and mean error values. Minimum temperature was the variable for which the CMIP6 models performed best, considering all metrics and all variables. All (100%) models presented r and KGE values above 0.8, thus confirming a high correlation between the data, also considering the variability, bias and magnitude of the errors. It also highlighted the CMCC-ESM2,

INM-CM4_8, INM-CM5 and NorESM2-NM models; which had very high correlation values (0.88; 0.89; 0.89 and 0.87, respectively) and KGE (0.86; 0.86; 0.88 and 0.86, respectively), this performance has already been verified graphically (Figure 4) in the previous sections.

Chart 1 – Statistical analysis of CMIP6 model data

Variable	Metric	ACCESS-ESM1-5	CMCC-ESM2	EC-EARTH3	INM-CM4_8	INM-CM5	IPSL-CM6A-LR	MIROC6	MPI-ESM1-2	MRI-ESM2	NorESM2-MM
pr	r	0.57	0.68	0.73	0.73	0.70	0.66	0.71	0.68	0.66	0.66
	Pbias	0.25	6.11	7.86	14.06	3.90	4.46	12.58	10.26	2.72	9.32
	KGE	0.55	0.56	0.53	0.40	0.56	0.56	0.61	0.61	0.59	0.40
	RMSE	2.99	2.91	2.82	3.19	2.83	2.91	2.67	2.74	2.82	3.37
hur	r	0.56	0.49	0.54	0.54	0.50	0.44	0.37	0.39	0.44	0.29
	Pbias	1.06	1.31	0.30	0.68	0.35	1.31	0.76	0.77	0.70	0.91
	KGE	0.38	0.28	0.25	0.30	0.20	0.15	0.19	0.31	0.27	0.21
	RMSE	4.84	5.40	5.34	5.15	5.65	6.01	5.83	5.22	5.42	5.69
rss	r	0.66	0.54	0.75	0.74	0.75	0.65	0.48	0.65	0.75	0.70
	Pbias	-0.82	-3.50	-2.30	-3.25	-1.97	-2.85	-3.82	-2.28	-2.50	-1.98
	KGE	0.63	0.50	0.74	0.73	0.74	0.65	0.38	0.64	0.73	0.69
	RMSE	2.30	2.33	1.92	1.98	1.88	2.16	2.38	2.12	1.80	2.08
sfcwind	r	0.57	0.42	0.31	-0.03	-0.07	0.41	0.55	0.37	0.55	0.44
	Pbias	-1.33	-2.36	-2.41	-4.49	-3.06	-0.96	-0.40	-0.25	-3.14	-2.56
	KGE	0.56	0.41	0.30	-0.06	-0.08	0.41	0.54	0.33	0.42	0.44
	RMSE	0.17	0.20	0.23	0.31	0.29	0.20	0.19	0.19	0.22	0.20
tasmax	r	0.64	0.66	0.55	0.55	0.61	0.59	0.57	0.64	0.69	0.75
	Pbias	2.24	1.03	0.99	0.49	0.99	1.14	-0.05	0.97	1.35	0.96
	KGE	0.61	0.64	0.55	0.54	0.58	0.58	0.53	0.63	0.69	0.71
	RMSE	2.25	1.89	2.32	2.16	1.99	2.11	2.03	2.12	1.86	1.84
tasmin	r	0.87	0.88	0.81	0.89	0.89	0.82	0.86	0.85	0.86	0.87
	Pbias	2.29	1.96	2.17	2.26	0.71	1.64	1.33	1.50	2.03	1.16
	KGE	0.87	0.86	0.81	0.86	0.88	0.81	0.86	0.84	0.84	0.86
	RMSE	1.59	1.59	1.92	1.56	1.49	1.82	1.63	1.72	1.58	1.61

Source: the authors

3.3 Ranking of the MCGs

The overall ranking of the GCMs for each variable was calculated based on the composite classification index CRI as to rank the performance of the models. For precipitation data (pr), the best ranked model was the EC-EARTH3, followed by the MIROC6 and INM-CM5 models. The INM-CM4_8, ACCESS-ESM1-5 and EC-EARTH models had, in this order, the best performance for relative humidity (hur) values. The INM-CM5 model was the best ranked for solar radiation (rss) data, followed by the EC-EARTH3 and MRI-ESM2 models.

For the analysis of maximum and minimum temperature, the model with the best performance was the INM-CM5, the CMCC-ESM2 also had an excellent performance for both variables (rank 2 and 3, respectively).

Table 3 – CMIP6 Model Ranking

Variable	Rank MCGs	r	Pbias	KGE	RMSE	Rank CRI
pr	EC-EARTH3	1	6	3	3	0.675
	MIROC6	2	9	1	1	0.675
	INM-CM5	4	2	4	4	0.650
	MPI-ESM1-2	5	8	2	2	0.575
	MRI-ESM2	8	1	5	5	0.525
	CMCC-ESM2	6	5	6	6	0.425
	IPSL-CM6A-LR	9	4	7	7	0.325
	ACCESS-ESM1-5	10	3	8	8	0.275
	INM-CM4_8	3	10	10	9	0.200
	NorESM2-MM	7	7	9	10	0.175
hur	INM-CM4_8	2	3	3	2	0.750
	ACCESS-ESM1-5	1	8	1	1	0.725
	EC-EARTH3	3	1	6	4	0.650
	MPI-ESM1-2	8	6	2	3	0.525
	INM-CM5	4	2	8	7	0.475
	MRI-ESM2	7	4	5	6	0.450
	CMCC-ESM2	5	10	4	5	0.400
	MIROC6	9	5	9	9	0.200
	NorESM2-MM	10	7	7	8	0.200
	IPSL-CM6A-LR	6	9	10	10	0.125
rss	INM-CM5	1	2	1	2	0.850
	EC-EARTH3	2	5	2	3	0.700
	MRI-ESM2	3	6	3	1	0.675
	NorESM2-MM	5	3	5	5	0.550
	INM-CM4_8	4	8	4	4	0.500
	ACCESS-ESM1-5	6	1	8	8	0.425
	MPI-ESM1-2	8	4	7	6	0.375
	IPSL-CM6A-LR	7	7	6	7	0.325
	CMCC-ESM2	9	9	9	9	0.100
	MIROC6	10	10	10	10	0.000
tasmax	ACCESS-ESM1-5	4	1	5	2	0.700
	MRI-ESM2	2	2	2	9	0.625
	CMCC-ESM2	3	4	3	8	0.550
	NorESM2-MM	1	8	1	10	0.500
	MPI-ESM1-2	5	7	4	4	0.500
	IPSL-CM6A-LR	7	3	6	5	0.475
	EC-EARTH3	10	5	8	1	0.400
	INM-CM5	6	6	7	7	0.350
	INM-CM4_8	9	9	9	3	0.250
	MIROC6	8	10	10	6	0.150

tasmin	ACCESS-ESM1-5	4	1	2	7	0.650
	CMCC-ESM2	3	5	3	6	0.575
	INM-CM4_8	1	2	6	9	0.550
	NorESM2-MM	5	9	4	5	0.425
	INM-CM5	2	10	1	10	0.425
	EC-EARTH3	10	3	10	1	0.400
	MIROC6	7	8	5	4	0.400
	MPI-ESM1-2	8	7	7	3	0.375
	MRI-ESM2	6	4	8	8	0.350
	IPSL-CM6A-LR	9	6	9	2	0.350
sfcwind	MRI-ESM2	1	4	1	1	0.825
	ACCESS-ESM1-5	2	2	2	2	0.800
	IPSL-CM6A-LR	7	1	7	3	0.550
	INM-CM5	5	5	5	4	0.525
	MIROC6	4	7	3	5	0.525
	MPI-ESM1-2	6	3	6	6	0.475
	CMCC-ESM2	3	9	4	7	0.425
	EC-EARTH3	8	6	8	8	0.250
	NorESM2-MM	10	8	10	9	0.075
	INM-CM4_8	9	10	9	10	0.050

Source: the authors

4 CONCLUSIONS

The focus of this research was to evaluate the performance of the CMIP6 climate models in simulating the monthly averages of precipitation, relative humidity, solar radiation, wind speed and maximum and minimum temperature for the observed period of 2000 to 2013, in the Cantareira System area, located in the state of São Paulo, Brazil. In general, the models captured the main seasonal trends for precipitation and temperature. The results also demonstrated a wide variation in the models' performance in their ability to simulate different climate variables, when evaluated by different statistical metrics.

For precipitation, the best model was the EC-EARTH and the worst was NorESM2-MM. For relative humidity, the best model was the INM-CM4_8, the worst was IPSL-CM6A-LR. The INM-CM5 model presented the best performance for simulating solar radiation data and the ACCESS-ESM1-5 the best for maximum temperature, MIROC6 had the worst performance for both. The ACCESS-ESM1-5 was also the best rated for minimum temperature, while IPSL-CM6A-LR was the worst. The MRI-ESM2 and INM-CM4_8 models had the best and worst performance for wind speed simulation, respectively.

Most models had difficulty simulating relative humidity and wind speed values, with poor performance for both variables and in all statistical metrics. For minimum temperature data, on the other hand, all models showed excellent performance, accurately simulating the observed values, with good correlation, little bias and low magnitude of errors.

Precipitation and temperature variables can be considered the most important, they are also the subject of study in most of the research that use CMIP6 climate models. In this study,

the highest-ranked climate models showed good performance in simulating these variables, especially minimum temperatures.

It is noted that in most cases, the worst-ranked models performed poorly in relation to statistical metrics, with little correlation to the observed data and a high magnitude of errors and bias (especially in extreme values). The use of any of these models may bring an unnecessary accumulation of uncertainty to the study.

Although the use of multi-model sets or ensembles is a common practice in the literature, as the use of more models tends to reduce and compensate for individual uncertainties, it is clear the importance of adequately selecting the models that are going to be used, which must be according to the particularities of the study. The joint use of models that have undergone prior performance evaluation tends to make the estimates more accurate and reliable.

The results of this research provide important information for users and developers of climate data and datasets (such as CLIMBra and Xavier). For developers, it is clear that further studies and research are still needed to improve the performance of climate models in different situations. For end users, prior evaluation and adequate selection of climate models for studies with future climate projections is essential.

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