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Validating the Mark-HadGEM2-ES and Mark-MIROC5 Climate Models to Simulate Rainfall in the Last Agricultural Frontier of the Brazilian North and North-East Savannah

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Authors' contributions

This work was carried out in collaboration among all authors. Author JFSS designed the study and wrote the first draft of the manuscript. Authors DCL and FASS managed the literature and data searches. Author LPN guided the making of the manuscript. All authors read and approved the final manuscript.

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ABSTRACT

The MarkSim climate data generator is designed to have global validity in scales of up to five degrees. Thus, the objective of this study was to evaluate the performance of the MarkSim-HadGEM2-ES and MarkSim-MIROC5 models to estimate average rainfall in the last agricultural frontier of the savannah in the north and north-east regions of Brazil. For this purpose, the simulated data were compared with those observed and recorded by the National Institute of Meteorology, being evaluated by statistical measures of correlation, bias and performance. The results revealed high bias and relative error, with unsatisfactory performance in the micro regional

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and regional scales. Calibration by means of regression improved performance and showed that in order to reproduce the current climate and make reliable projections in these spatial scales possible, there is a need to correct the systemic errors of these models.

Keywords: Validation; climate; modeling; savannah; rainfall.

1. INTRODUCTION

Over the past few decades, a large number of high-quality studies have been compiled to attest that climate change is unequivocal and can result in high-intensity social impacts in various areas such as energy, health and agriculture, for example. In this sense, perhaps the greatest consequence of the increase in regional and global temperatures is the alteration of the water cycle in several regions of the planet, increasing the frequency and intensity of extreme events such as floods and prolonged droughts [1-3].

The fifth phase of the Coupled Model Intercomparison Project (CMIP) coordinated experiments developed by several institutions for the development of Global Climate Models (GCM). In general, the GCMs have systematic errors and their spatial scales (e.g. 100 km per grid) are not adequate to project the behaviour of the local climate. As such, the use of GCMs without proper correction of their errors in regional studies and in the river basin scale is not recommended. It is, therefore, recommended the use of methods that correct these errors (i.e. downscaling, bias correction) [2,4].

Downscaling is characterized by the application of statistical or dynamic methods to increase the spatial resolution of the climate data set produced by a GCM [5-7]. The Model Output Statistics (MOS) is one of the statistical methods used to establish relations between data simulated by GCMs and those observed in local meteorological stations. For example, rainfall simulated by GCMs is not credible and represents averages in terms of grid area rather than local values but may contain information on actual rainfall. Thus, the local predictors can be calibrated from the regression between the observations and the predictors of a GCM so that this model can then be applied to future projections [8].

According to Silva [4], the 3rd order Markov generator, known as MarkSim, has shown good results in performing temporal and spatial downscaling in resolutions of up to 0.5°. Although it was not designed for this purpose, several studies [9-13] used it satisfactorily to estimate precipitation and temperatures aimed at evaluating the potential impacts of climate change on agricultural systems through the simulation of future scenarios.

Ongoing climate change is expected to increase the inter-annual variability of rainfall in many locations and to raise average annual temperatures at the global level in the near future. This phenomenon can have several impacts on plantations and livestock, such as lack or excess of water, outbreaks of pests and diseases, flooding of productive lands, forest fires, among others that threaten the health and well-being of populations [14-17].

The climate in the Brazilian savannah is particularly vulnerable to changes in land use and cover, since the water and temperature cycle is strongly influenced by the characteristics of vegetation [17-20,21]. Therefore, knowing and projecting the rainfall characteristics of this biome in the northern and north-eastern regions of Brazil becomes fundamental, because, in addition to the socio-economic implications, this information can serve as a subsidy for planning and formulation of public policies aimed at sustainable regional development [22,23].

In this context, the objective of this study was to assess the performance of rainfall simulations generated in the climate models MarkSim-HadGEM2-ES and MarkSim-MIROC5, based on data observed in conventional meteorological stations of the National Meteorological Institute (INMET) located in the micro-regions that make up the last agricultural frontier of the Brazilian savannah in the north and north-east regions.

2. MATERIALS AND METHODS

The study area is an important agricultural frontier in Brazil. The region comprises the Cerrado portions of the states of Maranhão, Tocantins, Piauí and Bahia. The region is composed of 337 municipalities distributed in an area of 73,848,967 hectares in 31 micro-regions (Fig. 1) and combine good geographical conditions for the cultivation of grains with relatively cheap land. It is also home to the last remaining undeveloped stretch of the Cerrado, thus creating tensions between production and environmental protection [2,24].

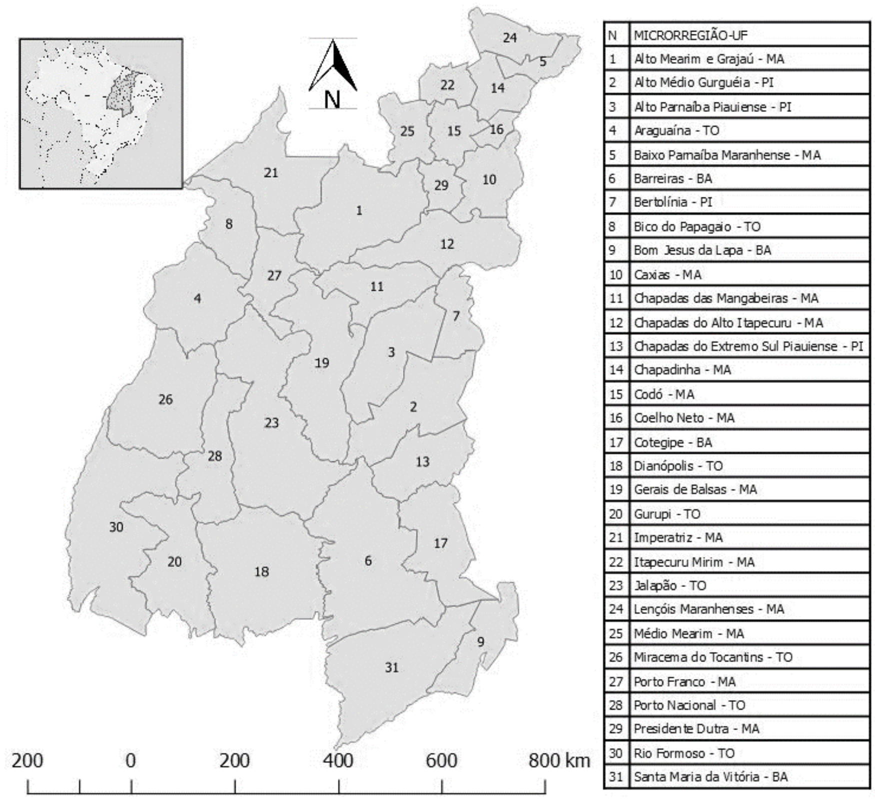

Fig. 1. Geographic location of the study area and its micro-regions [24]

The savannah formations are predominantly (63.6%) in the study area, but there are transition formations with different types of natural landscapes (25.7%) at the edge of the Amazon and Caatinga, to the west and east, respectively [25,26]. The relief is characterized by large areas of slopes (39%) and depressions (56%), with altitudes ranging from 1 to 1200 m above sea level. In the central extension, the semi-humid tropical climate is dominant and corresponds to about 78% of the territory, being characterized by periods of seven to eight months of scarce precipitation and average air temperature above 18°C in all the months of the year. On the eastern border, the semi-arid climate is characterised by the absence of rainfall for six months and high temperatures all year round. Four large hydrographic regions are contained within these limits, they are: Tocantins-Araguaia, Atlantic-North/Northeast stretch, Parnaíba and São Francisco [25,26].

The monthly precipitation was extracted from the records of the stations of the National Institute of Meteorology – INMET, available on the institution's website (http://www.inmet.gov.br/portal/). Historical records of observations made in 27 meteorological stations in the last ten years were used, referring to the period from January 2009 to December 2018. These records were associated with each micro-region (Fig. 1) which, according to information from the Municipal Agricultural Survey of the Brazilian Institute of Geography and Statistics [27], has experienced an agricultural area growth of over 40% since 2009.

The daily climate data simulation was generated in the MarkSim-GCM, whose detailed description can be found in the studies of Jones and Thornton [28-31]. The MarkSim -GCM was validated and calibrated from 10,000 weather stations worldwide with over 10 years of continuous data, grouped into 702 clusters of precipitation and temperature climates on a monthly scale. The MarkSim has been used efficiently as a temporal and spatial downscaling, with resolutions up to 50 km (http://gisweb.ciat.cgiar.org/MarkSimGCM/).

Therefore, temporal and special downscaling was used on the coordinates of the INMET stations, with a resolution of approximately 20 km, from the HadGEM2-ES (Hadley Centre Global Environmental Model 2 – Earth System) models with resolution data of 1,241°x1,875° [32] and MIROC5 (Model for Interdisciplinary Research on Climate 5) produced by the Climate System Research Center of the University of Tokyo, with resolution data of 1,406°×1,406° [33]. Thus, data on precipitation, solar radiation and maximum and minimum temperatures were generated for the period from January 2009 to December 2018.

It should be noted that MarkSim generates climatic data as of January 2010. As there was a need to obtain 2009 simulations, these were generated by regression, considering the data observed as a predictor variable of the simulations.

Descriptive statistics tools (mean, coefficient of variation, Student's t test and Pearson's correlation coefficient) were used in the Paleontological Statistics Software Package for Education and Data Analysis – PAST and used to analyse the results, adopting a significance level of 95% to test the possible inter-annual differences and relationships between the variables obtained and simulated.

To assess the accuracy of climate models, the percentage of bias (Pbias) and mean absolute error (MAE) was used together with Willmott's agreement index [34]. On the other hand, the adapted performance index (C') of the models was evaluated by the product of Pearson's correlation coefficient (r) and Willmott's index (d), as proposed by Camargo and Sentelhas [35].

The calibration of the models was performed through linear regression, where the predictive variable was the simulation generated. To test the independence of the residuals from the regression equation, the statistic of Durbin-Watson (D) was used [36].

The zero value for Pbias (Eq. 1) indicates the absence of bias, while different values indicate overestimation, when negative, and underestimation, when positive [37]. Considering that the observed data present a small margin of error, Pbias between ±0.5% were considered null.

$$P_{Bias} = 100(\sum Obsi - Esti / \sum Obsi) \quad (1)$$

Where: Esti – Estimated value of the variable for point i, Obsi – Observed value of the variable for point i.

The MAE measures the magnitude of the weighted average of absolute errors. For Willmott and Matsuura [38], the MAE is a natural and more accurate measure of the mean magnitude of the error as can be seen in Eq. 2.

$$MAE = \frac{1}{n} \sum_{i=0}^{n} |Oi - Ei| \quad (2)$$

Where: Ei – Estimated value of the variable for point i, Oi – Observed value of the variable for the point i, n – Sample size.

The mean absolute percentage error (MAPE) is a precision statistic that prevents the error from being decreased by the sum of values with opposite signs (Eq.3) and can be classified according to Table 1 [39].

$$MAPE = \frac{100}{n} \sum_{i=0}^{n} \left| \frac{(Obsi - Esti)}{Obsi} \right| \quad (3)$$

Where: Esti – Estimated value of the variable for point i, Obsi – Observed value of the variable for point i, n – Sample size.

Willmott's index reveals the degree of agreement between observed and simulated measurements, ranging from 0 to 1, where the first value represents the total disagreement and the second the perfect agreement. Thus, the higher the result of Eq.4, the better the performance of the model.

$$d = 1 - \frac{\sum_{i=1}^{n} (Obsi - Esti)^2}{\sum_{i=1}^{n} (|Esti - AObs| + |Obsi - AObs|)^2} \quad (4)$$

Where: Esti – Estimated value of the variable for point i, Obsi – Observed value of the variable for the point i, AObs – Average value of the observed variable n – Sample size.

The performance index - C' (Eq. 5), proposed by Camargo and Sentelhas [35], combines measures of precision and accuracy. In this sense, the precision measure was given by the well-known Pearson's linear correlation coefficient (R), which measures the degree of dispersion and direction of the dynamics of one variable in relation to another. The accuracy was represented by the Willmott's index, since it measures the degree of compliance between the estimated and observed data.

$$C' = d \times R \quad (5)$$

Table 1. Proposed classification for performance indicators

Pbias[1]	(C')[2]	MAPE[3]	Classification
<10%	> 0,75	< 10%	Very Good
10% - 14%	0,75 -0,64	10% - 19%	Good
15% - 24%	0,65 - 0,60	20% - 29%	Satisfactory
≥25%	< 0,60	≥30%	Unsatisfactory

[1][37], [2][35], [3][39]

Table 1 presents a summarized and harmonized classification of the evaluation proposals by Van Liew et al. [37], Lewis [39] and Camargo and Sentelhas [35] for the percentage of bias, mean absolute percentage error and performance index, respectively.

3. RESULTS AND DISCUSSION

The behaviour of mean rainfall observed monthly in the region and those simulated by the MarkSim-HadGEM2-ES and MarkSim-MIROC5 models is shown in Fig. 2. It can be seen that the simulations convincingly reflect the seasonality of the region [23,40]. In this sense, the simulations of the dry months (May to October) were characterized by a high level of reliability. However, both models were marked by strong biases of overestimation during the rainy months (October to April).

It was found that the MarkSim-HadGEM2-ES and MarkSim-MIROC5 models reproduce the same pattern of error, with small differences, with the rainy season being well reproduced only at the end of 2017 and beginning of 2018. The MarkSim simulator was designed to dispense the need for local calibration, having global validity [31]. However, the results presented in Fig. 2 reveal the need to calibrate the model for the region that configures the territorial delimitation of this study.

The rainy months correspond to the period of planting and development of crops, where the soil of large areas is covered and there is an accentuated humidity in the air due to the large vegetation coverage and consequently, abundant evapotranspiration [18,23,40-42].

MarkSim's pronounced tendency to overestimate rainfall in the rainy months of the region by running HadGEM2-ES and MIROC5 GCMs ends up being reflected in the monthly average projection. Accordingly, the descriptive statistics (Table 2) of the simulated and observed data reveal that the models simulate measures of central tendency and inter-annual variability very similar to each other, but higher than those observed, so that significant differences between the variables were detected at the minimum level of $p \leq 0,05$ in the student's t test, in this time scale.

The average annual volume precipitated in the region reaches 1,508 mm, monthly average of 126 mm (between 1950 and 1990). The rainy season occurs between October and May, with a monthly average of 163 mm, varying between 79 mm in May and 256 mm in March. The dry period occurs between June and September, a monthly average of 20 mm [43]. The annual and monthly averages observed in the period of this study were lower than those recorded between 1950 and 1990.

There is also a high intra- and inter-annual variability of rainfall in this region, which, according to Strassburg et al. [17], represents an indication of greater vulnerability to environmental changes, since the functioning of almost all ecosystem services is adapted to the patterns of spatial and temporal distribution of rainfall, as well as to the amplitude of its intensity.

The spatial bias of the models, in relation to the monthly average rainfall, on the scale of homogeneous micro-regions that presented agricultural expansion in the last ten years, can be observed in Fig. 3. Therefore, it was possible to verify that the models provided overestimated data for most, but not all, micro-regions. In some micro-regions there is underestimation of rainfall and in others the simulations precisely reproduce the intra-annual rainfall regime.

A simple comparison between the models showed the superiority of the MarkSim-HadGEM2-ES, since it did not show bias in eight micro-regions (Fig. 3B) while MarkSim-MIROC5 was successful in only five (Fig. 3A). Other five micro-regions had their rainfall underestimated in both models, being two central ones where savannahs predominate and three in the eastern border, in the transition from the Cerrado to the Semi-arid. It is also noted that the absence of bias (Pbias < 10%) is concentrated in the transitional micro-regions between the Cerrado and Amazon biomes [44].

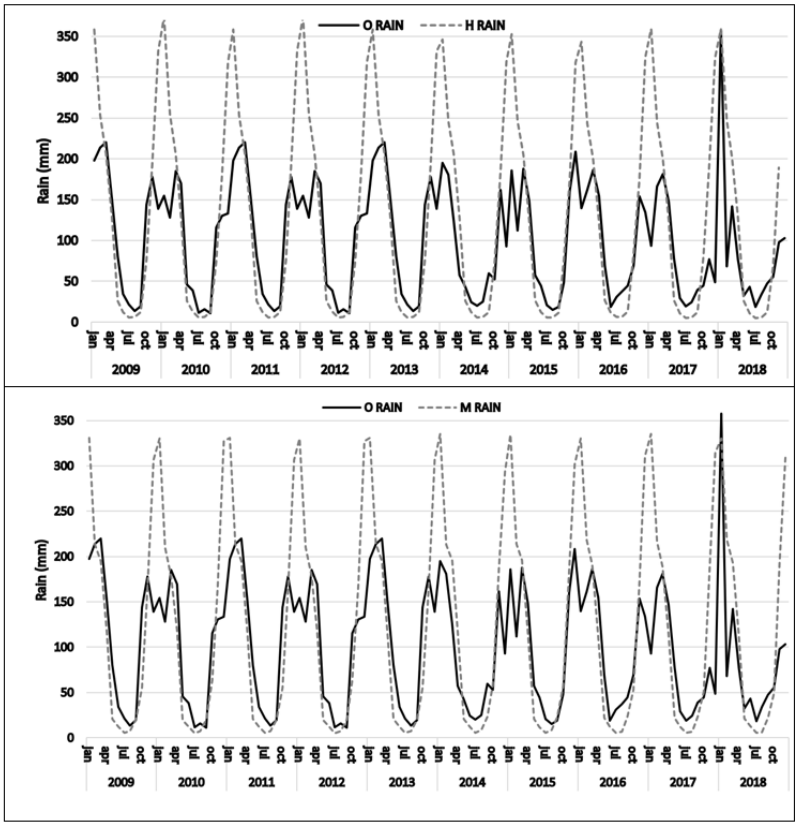

Fig. 2. Monthly averages of observed (O RAIN) and simulated rainfall by the MarkSim-HadGEM2-ES (H RAIN) and MarkSim-MIROC5 (M RAIN) models

Table 2. Descriptive statistics of the studied period

Indicators	MIROC5	HadGEM2	Observed
Monthly			
Average (mm)*	131,8[a]	122,1[a]	95,5[b]
SD (mm)	115,3	123,8	69,1
CV (%)	94,4	93,9	72,4
Annual			
Average (mm)*	1593,4[a]	1461,5[a]	1198,7[b]
SD (mm)	20,2	12,4	166
CV (%)	0,01	0,01	13,8

** Distinct letters represent significant differences (p ≤ 0,05)*

The values of the statistical indicators obtained for each model are shown in Table 3 and reveal that, on a regional scale, they are similar in relation to precision (d), determination (r^2) and the percentage of average error (MAPE). Only the last one is classified as unsatisfactory. However, they present significant differences in relation to the bias (Pbias), both being classified as unsatisfactory for this indicator [37]. The performance indicator was considered satisfactory [35]. Both models overestimate precipitation in most micro-regions, although they are considered good by Willmott's classification [34]. Thus, MarkSim-MIROC5 presents lower bias and confirms the findings of Sales et al. [45]. However, Torres [46] also found many uncertainties in the validation of climate models, even with dynamic downscaling techniques.

Table 4 shows that the percentage of bias was "unsatisfactory" in 13 micro-regions for each model used (MarkSim-HadGEM2-ES and MarkSim-MIROC5). However, it was found that in 15 micro-regions of Agricultural expansion, the bias of MarkSim-HadGEM2-ES is greater than that of MarkSim-MIROC5.

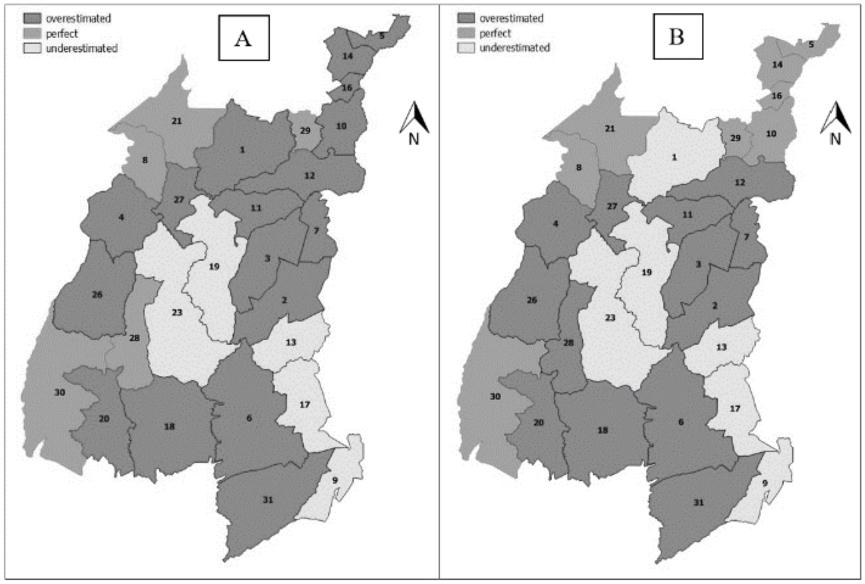

Fig. 3. Bias of monthly median precipitation simulated in MarkSim-MIROC5 (A) and MarkSim-HadGEM2-ES (B) models between 2009 and 2018

The average absolute error of HadGEM2-ES was higher than that of MarkSim-MIROC5 in 19 of these micro-regions. In the others, the difference in errors between the two models was irrelevant. The same occurred with the Willmott index [34], and the lowest values were located in micro-regions 02, 27 and 30.

Average errors above 70 mm, in at least one of the models, were found in 80.7% of the micro-regions. It is noteworthy that, even considering the high variability (CV > 70%) of the inter-annual rainfall averages observed in the study area (Table 2) by other authors [45,46], errors of this magnitude can be considered substantial, even though the agreement of the behaviour of the variables is high (d > 0.70), because they represent approximately 73% of the monthly mean value observed in the region.

The models were adjusted by testing multiple regression methods, with the polynomial method having the best performance in correcting the cyclical regime of oscillations in the region's precipitation. This was due to the behavior pattern of the errors in the time series (Fig. 2). Thus, the adjustment increased its agreement coefficient to 0.845 and 0.851 for the models MarkSim-HadGEM2-ES and MarkSim-MIROC5, respectively. The adjustment and quality coefficients generated for each model are expressed in the equations contained in Figs. 4C and 4D.

The calibration generated an increase in agreement between the simulations and the observed data (Table 5 and Fig. 5), which increased the performance level of the model and provided better temporal adjustments in seasonal oscillations.

Durbin-Watson's statistics resulted in values of 5.08 and 4.89 for the residuals of the calibration equations of the Mark-HadGEM2-ES and Mark-MIROC5 models, respectively. Thus, there is significant confidence ($p \leq 0,05$) that the residues do not present autocorrelation and that, therefore, the calibration equations are adequate [36].

Table 3. Model performance indicators in relation to the territorial delineation of the study

Indicators	MIROC5	HadGEM2	Performance
d	0,631	0,629	-
MAPE*	73,41	66,54	Unsatisfactory
R^2	0,722	0,724	-
Pbias*	-38,79	-27,26	Unsatisfactory
(C')	0,536	0,535	Unsatisfactory

**significative (p≤0,05)*

Table 4. Model performance indicators in each micro-region of agricultural expansion

ID	(d)		MAE (mm)		Pbias (%)	
	Had	**Miroc**	**Had**	**Miroc**	**Had**	**Miroc**
1	0,83	0,81	60,18	68,08	33,00	-39,84
2	0,29	0,26	83,15	87,35	-23,54	-24,19
3	0,56	0,61	139,99	140,34	18,69	18,12
4	0,89	0,88	73,93	86,58	19,40	12,34
5	0,87	0,87	81,12	76,98	-5,06	-31,82
6	0,79	0,78	71,61	70,32	-61,70	-49,31
7	0,68	0,67	85,10	89,66	-106,0	-112,8
8	0,87	0,88	64,12	59,48	-6,99	-8,88
9	0,81	0,80	62,10	55,94	45,61	18,00
10	0,85	0,87	81,59	72,86	-4,47	-22,59
11	0,56	0,61	139,99	140,34	18,69	18,12
12	0,80	0,80	67,15	70,57	-28,30	-38,17
13	0,69	0,73	67,89	53,23	90,56	49,31
14	0,87	0,87	81,12	76,98	-5,06	-31,82
16	0,87	0,87	81,12	76,98	-5,06	-31,82
17	0,80	0,81	63,82	62,90	42,73	22,42
18	0,38	0,41	150,41	126,97	-48,93	-37,55
19	0,51	0,46	127,79	123,40	25,92	26,69
20	0,87	0,85	83,13	76,36	-57,19	-37,10
21	0,87	0,88	64,12	59,48	-6,99	-8,88
23	0,87	0,90	82,56	72,87	16,47	28,21
26	0,89	0,89	82,25	88,40	-26,53	-18,59
27	0,45	0,43	192,65	188,05	-14,65	-12,16
28	0,86	0,89	94,63	75,33	-34,06	-7,18
29	0,86	0,86	94,15	92,92	-8,51	-6,46
30	0,38	0,41	150,41	126,97	-8,93	-7,55
31	0,64	0,60	86,73	71,33	-71,23	-28,52

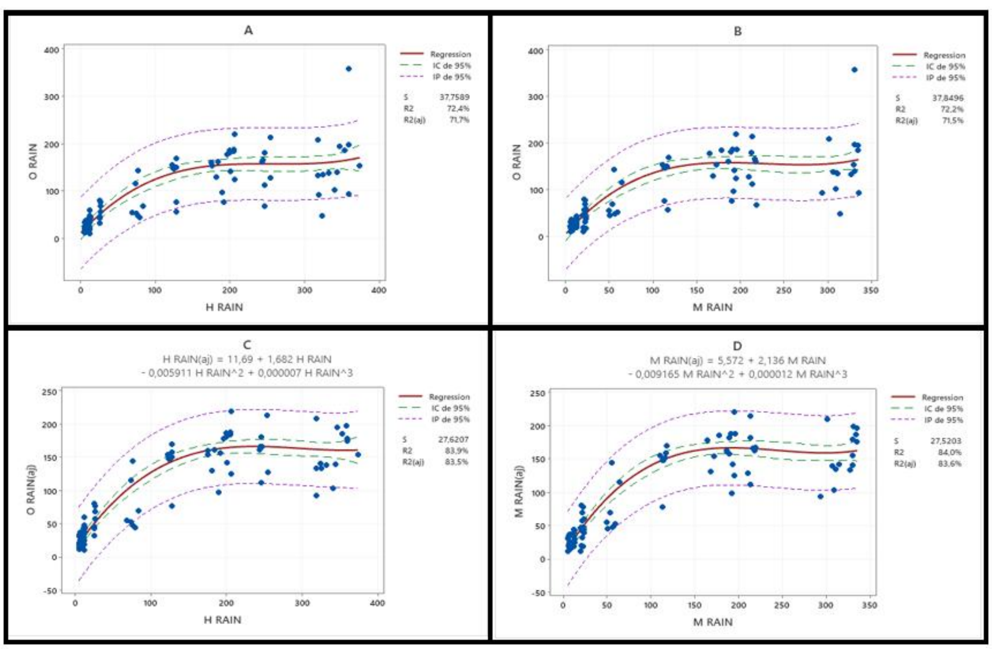

Fig. 4. Regression analysis between observed precipitation (O RAIN) and simulated by HadGEM2-ES (A) and MIROC5 (B) models. As well as the polynomial adjustment of the HadGEM2-ES (C) and MIROC5 (D) models with correction of the outliers

Table 5. Performance indicators in relation to the territorial delimitation of the study after the adjustment

Indicators	MIROC5	HadGEM2	Performance
d	0,851	0,845	Very Good
MAPE*	20,82	26,73	Satisfactory
R²	0,839	0,840	Very Good
Pbias*	-1,935	-9,667	Very Good
C'	0,779	0,774	Very Good

(p≤0,05)

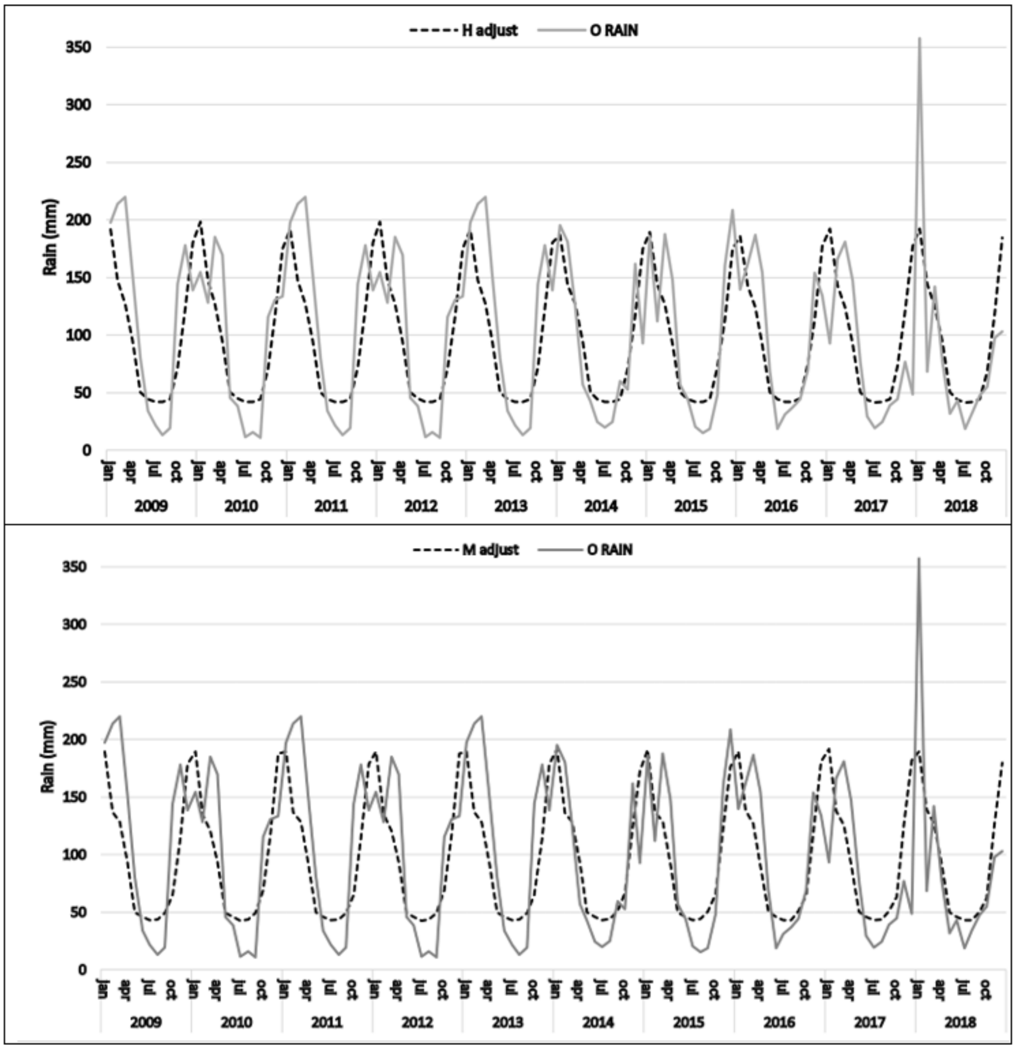

Fig. 5. Monthly averages of observed rainfall (O RAIN) and simulated by the adjusted models HadGEM2-ES (H adjust) and MIROC5 (M adjust)

4. CONCLUSION

Although both models reproduce well the seasonality of intra-annual precipitation, they present a high degree of overestimation in the rainy months and, despite presenting satisfactory levels of agreement in most micro regions, the bias was higher than 25% on a regional scale and varied from 5 to 112% on a micro-regional scale, being classified as "unsatisfactory" in most of the micro-regions analysed. The models have opposite biases in several micro-regions located at the northern limit of the study area, and in the regional scale the MarkSim-MIROC5 tends to have a lower overestimation.

The large biases of many micro-regions and in the region, determined a weak correlation between the data simulated by both models in relation to the observed data. This affected their performance coefficients, which were classified as unsatisfactory in all spatial scales analysed. This is reinforced by the values presented in the absolute average error, since the great variability of intra- and inter-annual precipitations determined errors greater than 70 mm in several of them. Therefore, the percentage of regional average error above 65% reinforces the unsatisfactory performance of the unadjusted models.

In this context, this study shows that the data generated in the climate models MarkSim-HadGEM2-ES and MarkSim-MIROC5 require correction of systematic errors prior to their use in regional projections aiming at multiple objectives, especially in the planning of public policies that require greater accuracy on the quantity and spatial and temporal distribution of rainfall. The adjustment of the data generated by the Mark-sim model, through polynomial regression and outlier correction, proved to be promising to improve its performance coefficients.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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