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Artigo

Estimation of Air Temperature Using Climate Factors in Brazilian Sugarcane Regions

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Abstract

This study aimed to estimate the minimum and maximum monthly air temperatures in the sugarcane regions of Brazil. A 30-year historical series (1988-2018) of maximum (Tmax) and minimum (Tmin) air temperatures from the NASA/POWER platform was used for 62 locations that produce sugarcane in Brazil. Multiple linear regression was used for data modeling, in which the dependent variables were Tmin and Tmax and the independent variables were latitude, longitude, and altitude. The comparison between estimation models and the real data was performed using the statistical indices MAPE (accuracy) and adjusted coefficient of determination (R2adj) (precision). The lowest MAPE values of the models for estimating the minimum air temperature occurred mainly in the North during February, March, and January. Also, the most accurate models for estimating the maximum air temperature occurred in the Southeast region during January, February, and March. The MAPE and R2adj values showed accuracy and precision in the models for estimating both the maximum and minimum temperatures, indicating that the equations can be used to estimate temperatures in sugarcane areas. The Tmin estimation model for the Southeast region in July shows the best performance, with a MAPE value of 1.28 and an R2adj of 0.94. The Tmax model of the North region for September presents higher precision and accuracy, with values of 1.28 and 0.96, respectively.

Keywords: modelling climate, multiple linear regression, sugarcane, latitude, longitude, air temperature.

Estimativa da Temperatura do Ar Utilizando Fatores Climáticos nas Regiões Canavieiras Brasileiras

Resumo

Este estudo visava estimar as temperaturas mínimas e máximas mensais do ar nas regiões canavieiras do Brasil. Uma série histórica de 30 anos (1988-2018) de temperaturas máximas (Tmax) e mínimas (Tmin) do ar da plataforma da NASA/POWER foi utilizada para 62 locais que produzem cana-de-açúcar no Brasil. A regressão linear múltipla foi utilizada para modelagem de dados, em que as variáveis dependentes eram Tmin e Tmax e as variáveis independentes eram a latitude, longitude e altitude. A comparação entre modelos de estimativa e os dados reais foi realizada utilizando os índices estatísticos MAPE (precisão) e coeficiente de determinação ajustado (R2adj) (precisão). Os valores MAPE mais baixos dos modelos para estimar a temperatura mínima do ar ocorreram principalmente no Norte durante Fevereiro, Março, e Janeiro. Também os modelos mais precisos para estimar a temperatura máxima do ar ocorreram na região Sudeste durante Janeiro, Fevereiro, e Março. Os valores MAPE e R2adj mostraram precisão e precisão nos modelos para estimar tanto a temperatura máxima como a mínima, indicando que as equações podem ser usadas para estimar as temperaturas em áreas de cana-de-açúcar. O modelo de estimativa de Tmin para a região Sudeste em Julho mostra o melhor desempenho, com um valor MAPE de 1,28 e um R2adj de 0,94. O modelo Tmax da região Norte para Setembro apresenta maior precisão e precisão, com valores de 1,28 e 0,96, respectivamente.

Palavras-chave: modelagem climática, regressão linear múltipla, cana de açúcar, latitude, longitude, temperatura do ar.

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1. Introduction

Climate is defined as the grouping of atmospheric dispositions, providing the characterization of a region (WMO345w, 2008; Werndl, 2016), influencing several economic, social, and environmental activities (Palinkas and Wong, 2020; Tol, 2018), especially the agribusiness. All stages of agricultural development suffer from climate interference (Schauberger *et al*., 2017; Syed *et al*., 2022), providing higher or lower crop yields (De Moraes *et al*., 2020; Yu *et al*., 2020).

Air temperature is one of the main weather elements related to plant development, interfering with its metabolic activities (Dos Santos *et al*., 2022; Zhao *et al*., 2017). The most affected processes are the maintenance respiration, transpiration, vegetative resting, phenological stage duration, flowering induction, and germination rate (Clemente, 2019; Pedro Júnior *et al*., 2004). Air temperature affects both the development and the quality of the final product (Figueirredo *et al*., 2008; Marcari; De Souza Rolim and De Oliveira Aparecido, 2015; Tabtiang *et al*., 2022). Night temperatures below 12 °C in the sugarcane cultivation lead to low photosynthetic rates, low respiration, and inhibition of protein metabolism (Guerra *et al*., 2014), thus reducing the accumulation of sucrose and, consequently, productivity (Sachdeva *et al*., 2011). On the other hand, average air temperatures below 21 °C during maturation assist in the accumulation of sucrose, which can be a stimulus for the beginning of this process (Araújo *et al*., 2016)

The Brazilian National Institute of Meteorology (INMET) has 779 meteorological stations distributed throughout Brazil, with one station every 10,925 km^2 (INMET, 2020). However, many of these stations have measurement failures or do not provide important variables, such as maximum and minimum air temperature, making studies of climate-agriculture relationships difficult (Bier and Ferraz, 2017). Different studies have been carried out to fill this scarcity of climate data by estimating the air temperature using variables that are easier to access, such as geographic data (Baghban *et al*., 2016).

Latitude, longitude, and altitude depend on air temperature and can be used for its estimation (Asfaw *et al*., 2019; Chen *et al*., 2022; Medeiros *et al*., 2005). Several authors have used these variables to estimate air temperature, for instance, Medeiros *et al*. (2005), who estimated the average air temperature for the Northeast of Brazil using multiple linear regression equations and obtained an adjusted coefficient of determination (R2adj) of 0.87.

Capuchinho *et al*. (2019) estimated the maximum (*Tmax*), minimum (*Tmin*), and average (*Tavg*) air temperatures also using multiple linear regression techniques and observed adjusted coefficients of determination ranging from 0.66 to 0.82 for *Tmax*, 0.56 to 0.72 for *Tmin*, and 0.66 to 0.74 for *Tavg*, with high precision and accuracy for the municipalities of Goiás. Another interesting paper, by Yu *et al*. (2021), who used a geographically weighted regression model to estimate the surface air temperature lapse rate in mainland China, concluded that the model had a strong predictive ability for surface air temperature.

Sugar and bioenergy are mainly produced using sugarcane (Karp *et al*., 2021; Menandro, 2016). Brazil is a world leader in sugarcane production due to its edaphoclimatic conditions and experience accumulated over the years (Cursi *et al*., 2022; De Oliveira Bordonal *et al*., 2018). Brazilian production in the 2018/2019 growing season was 746 million tons in a harvested area of around 10 million hectares (IBGE, 2020). Sugarcane is grown in all regions of Brazil, standing out the Southeast region, which represents 55% of all national production (CONAB, 2019).

Thus, it is clear that there is a need for an alternative way to collect air temperature in the sugarcane growing regions of Brazil. Given the importance of climate studies for sugarcane, coupled with the low number of meteorological stations in these regions. Thus the objective of this work is to estimate the maximum (*Tmax*) and minimum air temperature (*Tmin*) for the main sugarcane producing regions in Brazil.

2. Material and Methods

The study was carried out in 62 locations in Brazil with a significant sugarcane production (Fig. 1). The regions have 12 climate classes according to Köppen (1948), in which the tropical zone "A" is the predominant (Alvares *et al*., 2013). The Brazilian land area is 8,516,000 km^2, divided into five regions: Midwest, Northeast, North, South, and Southeast. The maximum (*Tmax*) and minimum air temperature (*Tmin*) data covered 30 years (1988-2018) and were collected from the National Aeronautics and Space Administration/Prediction of Worldwide Energy Resources (NASA/POWER platform) (Duarte and Sentelhas, 2020).

Multiple linear regression models were used to estimate Tmax and Tmin, using the least-squares method (Eq. (1)). The Dependent Variables consisted of *Tmax* and *Tmin*, while the Independent Variables consisted of the latitudes (decimal degrees), longitudes (decimal degrees), and altitudes (m). These variables were used to facilitate the use of the models. The models were calibrated by regions and months for high accuracy.

$$Y = a_1.X_1 + a_2.X_2 + a_3.X_3 + \ldots a_p.X_p \quad (1)$$

where Y is the dependent or predicted variable, X_1, X_2, X_3, …, X_p are the independent or explanatory variables, and a_1, a_2, a_3, …, a_p are the regression coefficients. Thus, the regression coefficients can be defined by the least-squares method from a set of n values of the variable Y associated

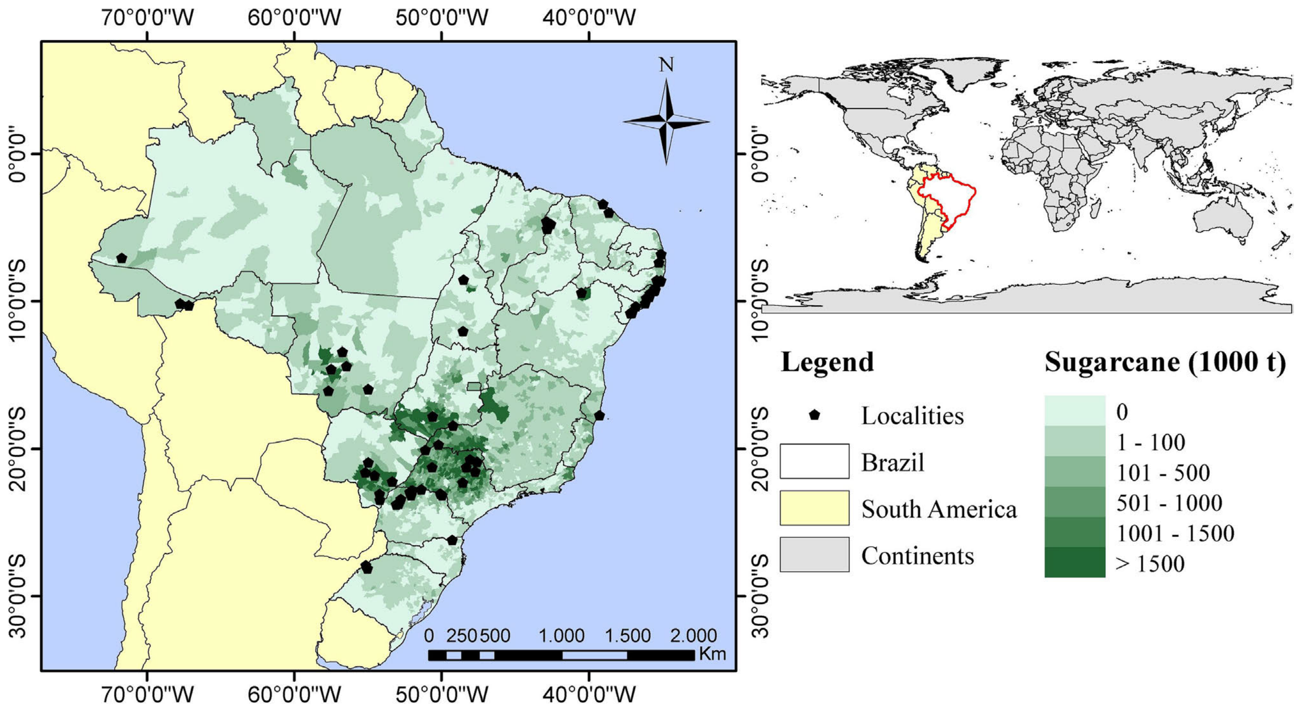

Figure 1 - Locations used in the study and municipal sugarcane production in Brazil.

with the corresponding n observations of the p independent variables.

Boxplot charts were constructed with the mean, median, and outliers of the maximum and minimum air temperature data, as this type of chart assists in analyzing the data distribution (Kampstra, 2008).

The comparison between the estimation models and the actual data was performed using the statistical indices accuracy and precision. Accuracy consists of how close the estimation is to the observed value, being evaluated by the mean absolute percentage error (MAPE) (Eq. (2)). Precision is the model's ability to repeat the estimation, being evaluated by the adjusted coefficient of determination (R2adj), according to Cornell and Berger (1987) (Eq. (3)).

$$R^2adj = \left[1 - \frac{\left(1 - R^2\right) \times (n-1)}{N - k - 1}\right] \quad (2)$$

$$MAPE(\%) = \frac{\sum_{i=1}^{n} \cdot \left(\left|\frac{Yest_i - Yobs_i}{Yobs_i}\right| \times 100\right)}{N} \quad (3)$$

where $Yest_i$ is the estimated air temperature, $Yobs_i$ is the observed air temperature, n is the number of data points, and k is the number of independent variables in the regression.

Maps of variation of the minimum and maximum air temperature between the sample points were generated to verify the distribution of the data, using the geographic information system (GIS). The flowchart explaining the steps of the work can be seen in Fig. 2.

3. Results and Discussion

The maximum and minimum air temperatures in the studied locations ranged from 23 to 33 °C and 8 to 24 °C, respectively (Fig. 3). July showed the lowest values of *Tmin* (16.75 °C) and *Tmax* (26.06 °C). January had the highest *Tmin* (22.20 ° C) and October, the highest *Tmax* (31.56 °C). August (11.45 °C) and September (11.52 °C) presented the highest average thermal amplitude. Ramos *et al*. (2018) observed a high amplitude in the North and South regions, as reported in this study. Moraes *et al*. (2020) also observed similar temperature variations in the North of Brazil.

The regions showed different average values for *Tmax* and *Tmin* over the year. Municipalities located in the Northeast had the highest *Tmax*, with an average of 31.32 ± 3.28 °C. November and December were the warmest months in the region, with averages of 31.01 ± 3.47 °C and 31.03 ± 2.71 °C, respectively (Fig. 3B). Guimarães *et al*. (2016) found similar results. The Southeast region showed a significant decrease in *Tmin* and *Tmax* from May to September, as reported by Aparecido *et al*. (2014).

The locations Santo Amaro das Brotas (SE) and São Luís do Quitunde (AL) showed the highest average values for *Tmax*, with averages of 32.47 ± 2.82 °C and 32.53 ± 2.93 °C, respectively. These temperatures are

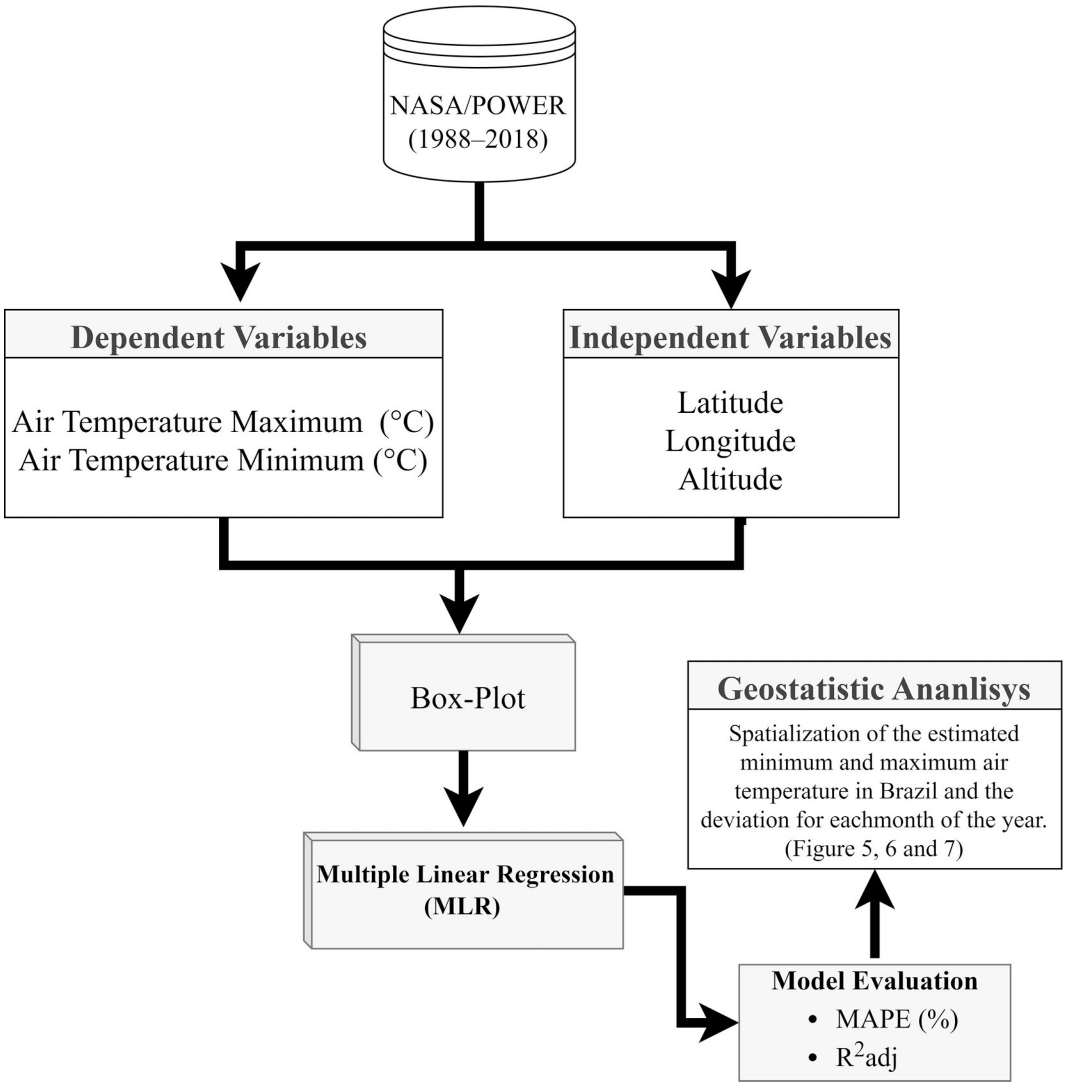

Figure 2 - Flowchart representing the stages for the accomplishment of the work.

within the appropriate range for good sugarcane development (Teodoro 2015). The municipality of Santo Amaro das Brotas (SE) stood out with expressive sugarcane production, reaching 1.3 million tons (IBGE, 2018).

The estimated and actual *Tmax* and *Tmin* on a national scale were compared for the analyzed municipalities. The estimation model was close to reality in most locations (Figs. 4-5, Tables 1 and 2).

The precision (R2adj) and accuracy (MAPE) of the Tmin estimation models showed a high variation relative to the regions and months (Table 1). Models from the Midwest and Northeast regions showed less accuracy, with MAPE values of 0.76 ± 0.18 and 5.50% ± 291, respectively. The Northeast presented values of 0.71 ± 0.13 and 6.44% ± 3.68, respectively. On the other hand, the models calibrated for the North and Southeast showed higher precision, with R2adj values of 0.93 ± 0.05 and 0.78 ± 0.19. These regions also showed higher accuracy, with an average MAPE of 3.92% ± 2.48 for the North and 2.94% ± 1.37 for the Southeast. A MAPE value below 5% is considered low, as described by Aparecido *et al*. (2020); Moreto and Rolim, (2015).

Latitude was the variable that most influenced the *Tmin* estimation in the Southeast and Midwest. A 10° variation in latitude led to a *Tmin* variation of around 2.8 °C in the Southeast and 2.3 °C in the Midwest (Table 1). In October, latitude showed a strong influence on the *Tmin* estimation for the Northeast and South ($p < 0.05$), with Tmin varying around 1.16 and 2.46 °C, with an increase of 10° in latitude, respectively.

In general, May, June, and July showed the highest precision (Fig. 4), with average adjusted coefficients of determination (R2adj) of 0.92 ± 0.07, 0.88 ± 0.11, and 0.89 ± 0.14, respectively. On the other hand, January, February, and March presented the most accurate models (Fig. 5A,B,C), with average MAPE values of 2.20 ± 0.67,

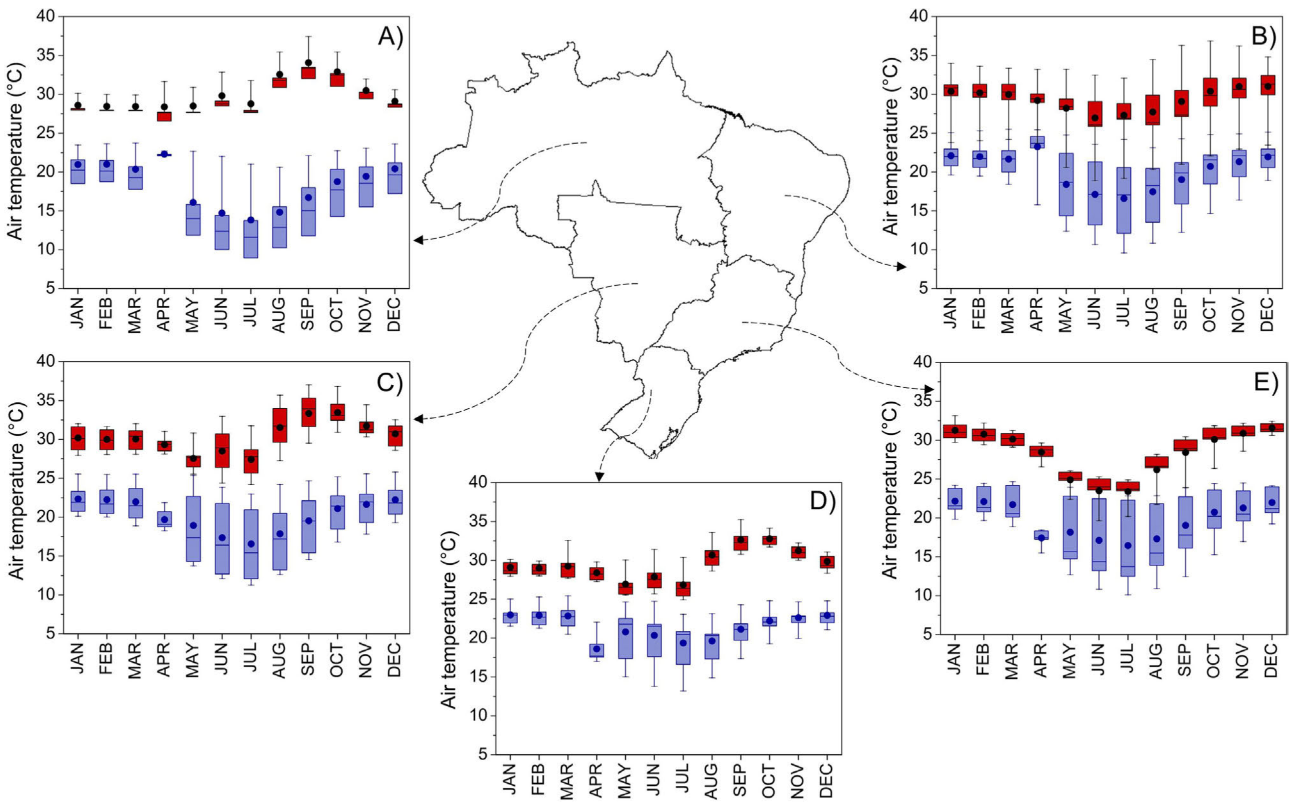

Figure 3 - Seasonal distribution of minimum and maximum air temperatures for locations grouped by regions in Brazil. Legend: A) North, B) Northeast, C) Midwest, D) South, and E) Southeast.

1.92 ± 0.81, and 2.92 ± 0.57, respectively. Moreover, these months had high precision, with average R2adj values of 0.86 (0.09) for January, 0.86 ± 0.05 for February, and 0.85 ± 0.09 for March. Lima and Ribeiro (1998) concluded that these months have the highest adjusted coefficient of determination when estimating *Tmin*, but the model precision was lower, with values of 0.77 for January, 0.84 for February, and 0.82 for March.

The regions with the highest and lowest MAPE in January were Southeast (1.28) and North (2.75). The coldest month (June) presented the lowest average accuracy (7.73) (Fig. 3G), varying from 4.17 to 12.44, which correspond to the Southeast and Northeast, respectively. The *Tmin* estimation model with the highest precision (0.92) and highest accuracy (0.76) was observed for the North in February (Fig. 4B).

The precision and accuracy of the calibrated models to estimate *Tmax* varied according to the regions and period of the year (Fig. 5, Table 2). The North and Southeast regions had the highest average values for the adjusted coefficient of determination, with values of 0.92 ± 0.06 and 0.82 ± 0.04. Also, the models of these regions presented the highest accuracy, with average MAPE values of 1.27 ± 1.26 and 1.09 ± 0.82 for the North (Table 2). Conversely, the models of the Northeast and Midwest showed the lowest precision and accuracy, with average R2adj and MAPE values of 0.29 ± 0.13 and 5.96 ± 1.79 for the Northeast and 0.53 ± 0.22 and 4.75 ± 4.47 for the Midwest. Antonini *et al*. (2009) calibrated models to estimate the air temperature in the state of Goiás (Midwest region) and obtained an intermediate precision (R2adj from 0.60 to 0.62) when subjected to high and low altitudes.

The models calibrated for the Midwest and Southeast in December showed that the latitude factor had the highest influence in the *Tmax* estimation, as observed by coefficients of the regression equation. In this case, a 10° increase in latitude led to a variation of 2.85 and 4.68 °C, respectively, in *Tmax* estimation. The models calibrated for the Southeast and North region were significant. The regression equations of locations in the Northeast showed an increase in R2adj for April, June, July, and August, a trend also observed by Medeiros *et al*. (2005).

The models calibrated for January, June, and July obtained higher precision, with R2adj values of 0.72 ± 0.31, 0.72 ± 0.27, and 0.71 ± 0.28, respectively (Fig. 5A, G, I). On the other hand, November (0.56), March (0.58), and April (0.61) showed the lowest precision (Fig. 4C, D). The average accuracy of the models calibrated for the summer months was higher than the other months of the year, with MAPE values of 1.95% ± 1.91 for December, 1.62% ± 1.45 for January, and 1.69% ± 1.56 for February. In contrast, the models for

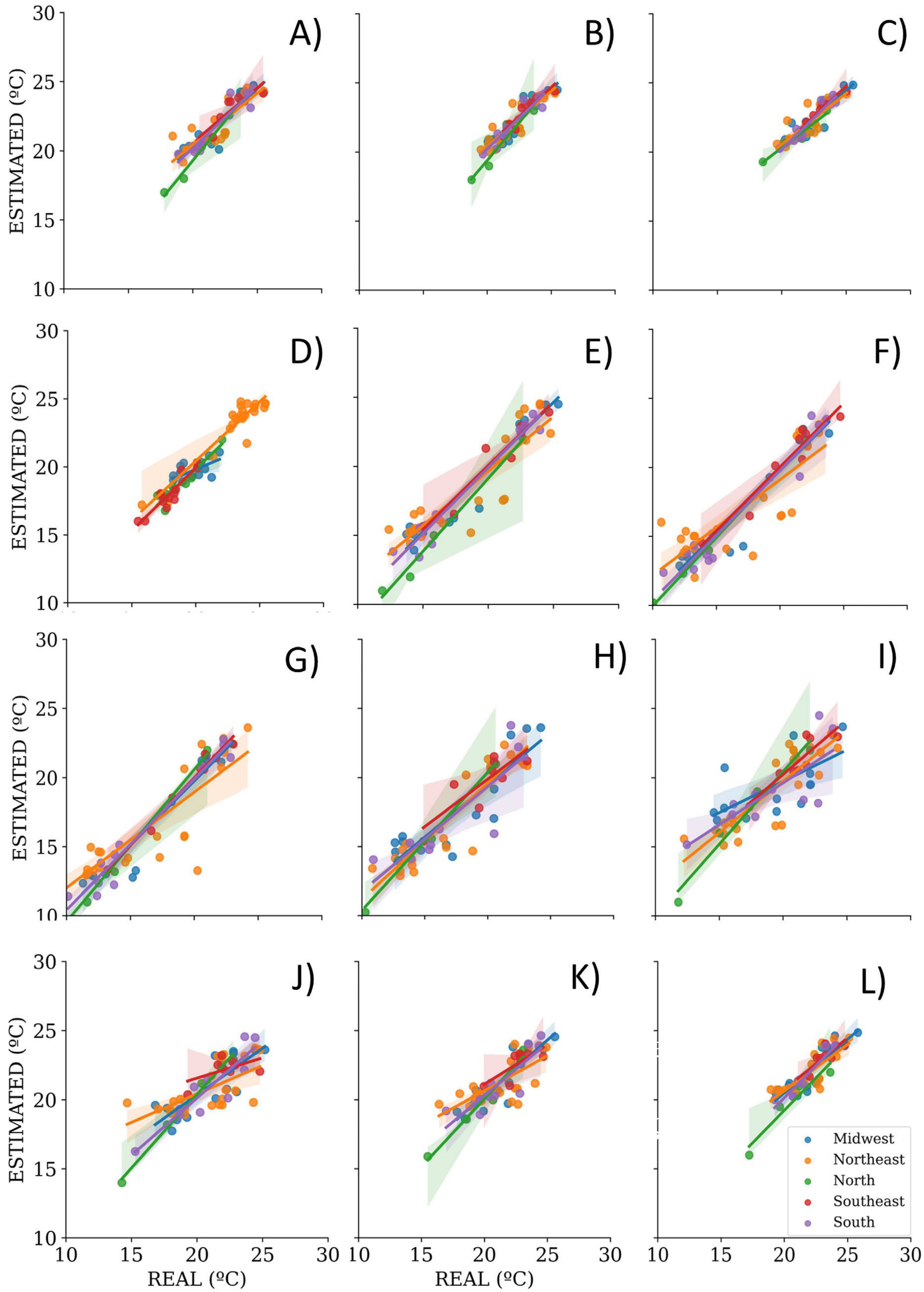

Figure 4 - Relationship of the estimated and actual minimum air temperature in Brazil as a function of the month: A) January, B) February, C) March, D) April, E) May, F) June, G) July, H) August, I) September, J) October, K) November, and L) December.

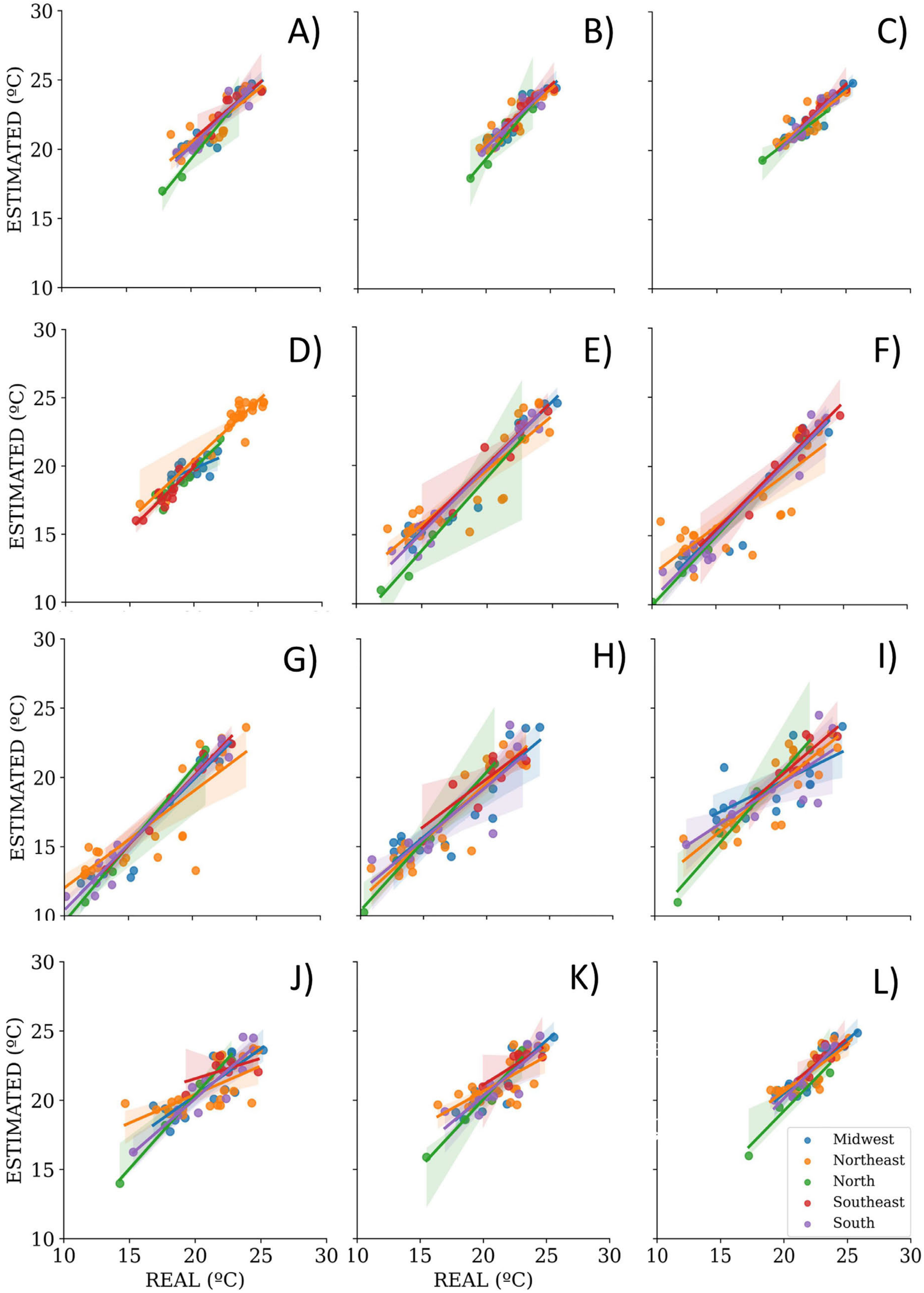

Figure 5 - Relationship of the estimated and actual maximum air temperature in Brazil as a function of the month: A) January, B) February, C) March, D) April, E) May, F) June, G) July, H) August, I) September, J) October, K) November, and L) December.

Table 1 - Models calibrated to estimate the minimum air temperature in Brazil for each region and as a function of the months of the year.

Region	Model	p-value	Mape (%)	R^2adj
	January			
North	0.045LAT + 0.234LONG + 0.002ALT + 26.574	0.002	2.75	0.96
Northeast	0.025LAT + 0.038LONG - 0.004ALT + 25.804	0.001	2.54	0.74
Midwest	0.067LAT + 0.042LONG - 0.004ALT + 26.826	0.001	2.73	0.80
Southeast	0.048LAT + 0.081LONG - 0.002ALT + 27.024	0.022	1.28	0.89
South	0.064LAT + 0.056LONG - 0.003ALT + 26.70	0.002	1.69	0.91
Average			2.20	0.86
	Fevereiro			
North	0.044LAT + 0.228LONG - 0.001ALT + 26.768	0.001	0.76	0.92
Northeast	0.037LAT + 0.049LONG - 0.006ALT + 26.439	0.001	2.53	0.80
Midwest	0.093LAT + 0.072LONG + 0.002ALT + 27.672	0.001	2.83	0.84
Southeast	0.325LAT - 0.446LONG - 0.002ALT + 5.153	0.042	1.70	0.85
South	0.101LAT + 0.079LONG - 0.003ALT + 28.865	0.003	1.79	0.89
Average			1.92	0.86
	March			
North	0.222LAT + 0.157LONG + 0.004ALT + 32.249	0.001	3.37	0.97
Northeast	0.076LAT + 0.075LONG - 0.005ALT + 27.999	0.001	3.42	0.75
Midwest	0.041LAT + 0.036LONG - 0.007ALT + 26.520	0.001	3.2	0.84
Southeast	0.110LAT + 0.125LONG + 0.000ALT + 29.410	0.077	2.41	0.79
South	0.099LAT + 0.115LONG + 0.005ALT + 29.235	0.086	2.22	0.88
Average			2.92	0.85
	April			
North	0.057LAT + 0.055LONG + 0.028ALT + 21.458	0.001	2.69	0.87
Northeast	0.209LAT + 0.234LONG - 0.008ALT + 34.782	0.001	2.61	0.87
Midwest	0.276LAT + 0.270LONG - 0.006ALT + 42.265	0.154	3.77	0.39
Southeast	0.235LAT + 0.340LONG - 0.007ALT + 40.769	0.024	2.49	0.89
South	0.303LAT + 0.285LONG - 0.001ALT + 40.399	0.048	2.33	0.71
Average			2.78	0.75
	May			
North	0.068LAT + 0.273LONG - 0.009ALT + 28.155	0.001	7.43	0.93
Northeast	0.259LAT + 0.193LONG - 0.002ALT + 33.666	0.001	8.22	0.79
Midwest	0.305LAT + 0.287LONG +0.002ALT + 36.682	0.001	4.75	0.94
Southeast	0.031LAT + 0.061LONG - 0.018ALT + 5.153	0.011	3.51	0.92
South	0.101LAT + 0.079LONG - 0.003ALT + 26.807	0.001	4.73	0.96
Average			5.73	0.91
	June			
North	0.403LAT + 0.356LONG + 0.005ALT + 40.268	0.001	9.84	0.93
Northeast	0.149LAT + 0.157LONG - 0.010ALT + 30.417	0.001	12.44	0.69
Midwest	0.226LAT + 0.226LONG - 0.006ALT + 33.068	0.001	6.63	0.91
Southeast	0.282LAT + 0.223LONG - 0.001ALT + 33.407	0.011	4.17	0.92
South	0.350LAT + 0.402LONG - 0.001ALT + 40.278	0.002	5.56	0.94
Average			7.73	0.88

(*continued*)

Table 1 - continued

Region	Model	p-value	Mape (%)	R^2adj
	July			
North	0.301LAT + 0.301LONG + 0.005ALT + 33.227	0.001	3.68	0.95
Northeast	0.045LAT + 0.234LONG + 0.002ALT + 32.023	0.001	13.03	0.65
Midwest	0.231LAT + 0.217LONG - 0.005ALT + 31.935	0.001	6.32	0.93
Southeast	0.097LAT + 0.146LONG - 0.008ALT + 27.720	0.002	1.28	0.96
South	0.359LAT + 0.343LONG + 0.002ALT + 37.720	0.002	5.40	0.96
Average			5.94	0.89
	August			
North	0.044LAT + 0.228LONG - 0.001ALT + 26.768	0.001	3.35	0.98
Northeast	0.037LAT + 0.049LONG - 0.006ALT + 26.439	0.001	7.25	0.84
Midwest	0.213LAT + 0.160LONG - 0.004ALT + 30.729	0.002	10.27	0.76
Southeast	0.010LAT - 0.054LONG - 0.008ALT + 22.185	0.163	5.85	0.69
South	0.262LAT + 0.222LONG - 0.003ALT + 34.141	0.023	8.60	0.76
Average			7.06	0.81
	September			
North	0.273LAT + 0.275LONG + 0.005ALT + 33.853	0.001	4.86	0.96
Northeast	0.225LAT + 0.201LONG + 0.001ALT + 31.826	0.001	7.45	0.74
Midwest	0.068LAT + 0.084LONG - 0.009ALT + 27.517	0.097	11.8	0.45
Southeast	0.124LAT + 0.036LONG - 0.0001ALT + 25.259	0.075	3.7	0.79
South	0.230LAT + 0.252LONG + 0.001ALT + 35.316	0.114	9.54	0.6
Average			7.47	1.19
	October			
North	-0.720LAT + 1.050LONG + 0.000ALT + 6.336	0.001	2.33	0.91
Northeast	0.116LAT + 0.090LONG - 0.002ALT + 28.341	0.016	8.05	0.41
Midwest	0.184LAT + 0.167LONG + 0.004ALT + 30637	0.002	5.86	0.67
Southeast	-0.025LAT - 0.030LONG - 0.012ALT + 22.278	0.672	4.01	0.29
South	0.246LAT + 0.238LONG + 0.004ALT + 35.660	0.010	4.63	0.83
Average			4.98	0.62
	November			
North	0.491LAT + 0.338LONG + 0.003ALT + 48.038	0.001	2.09	0.96
Northeast	0.088LAT + 0.106LONG - 0.002ALT +28.343	0.003	6.17	0.51
Midwest	0.055LAT + 0.022LONG - 0.007ALT + 25.817	0.002	4.02	0.80
Southeast	0.030LAT + 0.017LONG - 0.003ALT + 24.332	0.291	2.93	0.57
South	0.164LAT + 0.130LONG - 0.001ALT+ 31.038	0.027	4.04	0.76
Average			3.85	0.72
	December			
North	-0.334LAT + 1.120LONG - 0.004ALT + 30.735	0.001	3.87	0.92
Northeast	0.098LAT + 0.075LONG - 0.001ALT + 27.831	0.001	3.62	0.67
Midwest	0.070LAT + 0.047LONG - 0.004ALT + 27.078	0.001	3.86	0.78
Southeast	0.015LAT + 0.045LONG - 0.005ALT + 25.294	0.107	1.92	0.75
South	0.069LAT + 0.003LONG - 0.001ALT + 26.167	0.001	1.81	0.93
Average			3.02	0.81

Table 2 - Models calibrated to estimate the maximum air temperature in Brazil for each region and as a function of the months of the year.

Region	Model	p-value	Mape (%)	R^2adj
	January			
North	0.547LAT + 0.574LONG - 0.0961ALT + 89.657	0.001	0.44	0.94
Northeast	0.080LAT + 0.046LONG + 0.008ALT + 32.758	0.194	4.10	0.19
Midwest	-0.331LAT - 0.329LONG - 0.002ALT + 7.252	0.001	1.49	0.85
Southeast	-0.348LAT - 0.474LONG - 0.003ALT + 3.812	0.024	0.75	0.88
South	-0.213LAT - 0.223LONG - 0.001ALT + 14.665	0.038	1.30	0.73
Average			1.62	0.72
	Fevereiro			
North	0.388LAT + 0.409LONG -0.061ALT + 70.561	0.001	0.54	0.94
Northeast	0.077LAT + 0.058LONG + 0.006ALT + 32.987	0.339	4.38	0.14
Midwest	-0.297LAT - 0.296LONG - 0.002ALT + 9.182	0.001	1.25	0.86
Southeast	-0.325LAT - 0.446LONG - 0.002ALT + 5.153	0.036	0.74	0.86
South	0.180LAT - 0.189LONG +0.001 + 16.488	0.084	1.55	0.64
Average			1.69	0.69
	March			
North	0.119LAT + 0.122LONG - 0.002ALT + 37.775	0.001	0.55	0.94
Northeast	0.055LAT + 0.043LONG + 0.003ALT + 32.273	0.574	4.71	0.08
Midwest	-0.228LAT - 0.217LONG - 0.004ALT + 15.325	0.009	1.61	0.67
Southeast	0.118LAT + 0.245LONG - 0.005ALT + 42.910	0.016	1.31	0.91
South	-0.036LAT - 0.052LONG - 0.0001ALT + 26.876	0.513	1.78	0.30
Average			1.99	0.58
	April			
North	0.381LAT + 0.398LONG - 0.053ALT + 68.086	0.001	0.87	0.85
Northeast	0.108LAT + 0.096LONG + 0.007ALT + 33.548	0.101	4.05	0.24
Midwest	-0.101LAT - 0.100LONG - 0.003ALT + 23.324	0.028	17.76	0.58
Southeast	-0.033LAT - 0.017LONG - 0.004ALT + 28.823	0.036	0.80	0.86
South	0.140LAT + 0.120LONG + 0.003ALT + 37.322	0.221	2.21	0.50
Average			5.14	0.61
	May			
North	0.902LAT + 0.953LONG - 0.162ALT + 130.111	0.001	4.86	0.77
Northeast	0.194LAT + 0.162LONG + 0.013ALT + 35.642	0.001	4.11	0.53
Midwest	0.278LAT + 0.273LONG - 0.005ALT + 50.152	0.292	3.40	0.30
Southeast	0.433LAT + 0.615LONG - 0.007ALT + 63.771	0.013	1.10	0.91
South	0.382LAT + 0.362LONG - 0.0006ALT + 53.591	0.022	2.06	0.78
Average			3.11	0.66
	June			
North	1.987LAT + 2.103LONG - 0.397ALT + 260.834	0.001	1.13	0.97
Northeast	0.211LAT + 0.154LONG + 0.0159ALT + 34.660	0.001	5.69	0.50
Midwest	0.465LAT - 0.458LONG - 0.007ALT + 64.308	0.205	5.16	0.35
Southeast	0.720LAT + 1.033LONG - 0.006ALT + 86.847	0.010	1.31	0.93
South	0.506LAT + 0.484LONG - 0.0008ALT + 61.616	0.008	2.42	0.84
Average			3.14	0.72

(*continued*)

Table 2 - continued

Region	Model	p-value	Mape (%)	R^2adj
		July		
North	2.994LAT + 3.168LONG - 0.615ALT + 383.084	0.001	1.13	0.94
Northeast	0.200LAT + 0.123LONG + 0.018ALT + 33.052	0.009	7.23	0.40
Midwest	0.618LAT + 0.604LONG - 0.008ALT + 76.652	0.134	6.00	0.41
Southeast	0.855LAT + 1.233LONG + 0.006ALT 98.729	0.010	1.31	0.93
South	0.623LAT + 0.598LONG - 0.001ALT + 70.626	0.005	2.63	0.87
Average			3.66	0.71
		August		
North	2.547LAT + 2.682LONG - 0.513ALT + 330.612	0.001	2.30	0.91
Northeast	0.155LAT + 0.055LONG + 0.021ALT + 30.777	0.041	8.52	0.31
Midwest	0.183LAT + 0.184LONG + 0.001ALT + 44.427	0.323	6.07	0.25
Southeast	0.848LAT + 1.247LONG - 0.006ALT + 101.551	0.014	1.16	0.91
South	0.669LAT + 0.641LONG - 0.0002 + 79.397	0.006	2.82	0.86
Average			4.17	0.65
		September		
North	1.935LAT + 2.023LONG - 0.367ALT + 255.211	0.001	1.33	0.98
Northeast	0.145LAT + 0.036LONG + 0.023ALT + 31.192	0.052	8.60	0.29
Midwest	0.540ALT + 0.529LONG - 0.006ALT + 75.108	0.134	4.56	0.41
Southeast	0.778LAT + 1.165LONG -0.006ALT + 98.636	0.021	1.12	0.89
South	0.648LAT + 0.617LONG + 0.0005ALT + 76.627	0.012	2.94	0.82
Average			3.71	0.68
		October		
North	1.893LAT + 1.978LONG - 0.369ALT + 251.344	0.001	1.22	0.98
Northeast	0.109LAT + 0.008LONG + 0.019ALT + 31.273	0.101	7.82	0.24
Midwest	0.127LAT + 0.130LONG - 0.003ALT + 43.894	0.122	2.89	0.43
Southeast	0.051LAT + 0.463LONG - 0.003ALT + 41.353	0.067	0.91	0.80
South	0.493LAT + 0.457LONG + 0.0008ALT + 65.75	0.029	2.65	0.76
Average			3.10	0.64
		November		
North	0.611LAT + 0.631LONG - 0.106ALT + 98.090	0.001	0.58	0.89
Northeast	0.217LAT + 0.130LONG + 0.019ALT + 37.309	0.019	7.12	0.34
Midwest	-0.062LAT - 0.064LONG - 0.005ALT + 29.249	0.150	5.06	0.43
Southeast	-0.097LAT - 0.067LONG - 0.005ALT + 27.812	0.004	0.84	0.81
South	0.142LAT - 0.154LONG + 0.010ALT + 15.386	0.001	2.71	0.30
Average			3.26	0.56
		December		
North	0.968LAT + 1.018LONG - 0.189ALT + 141.114	0.001	0.26	0.98
Northeast	0.098LAT + 0.032LONG + 0.013ALT + 32.971	0.072	5.18	0.26
Midwest	-0.285LAT - 0.285LONG -0.003ALT + 11.381	0.001	1.72	0.80
Southeast	-0.469LAT - 0.646LONG - 0.003ALT - 4.695	0.017	0.85	0.90
South	0.008LAT - 0.005LONG - 0.0007ALT + 31.946	0.783	1.73	0.15
Average			1.95	0.62

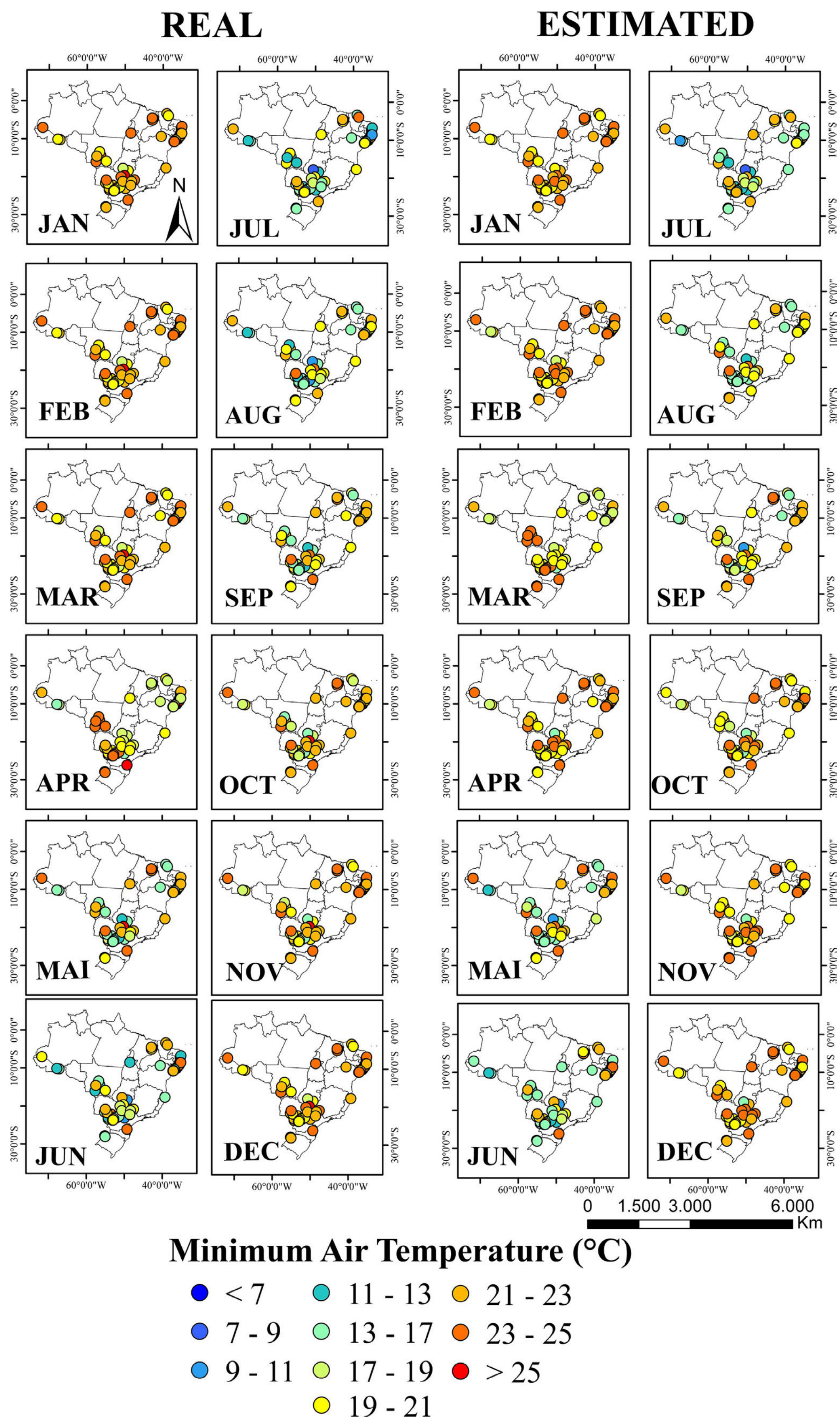

Figure 6 - Spatialization of the estimated minimum air temperature in Brazil for each month of the year.

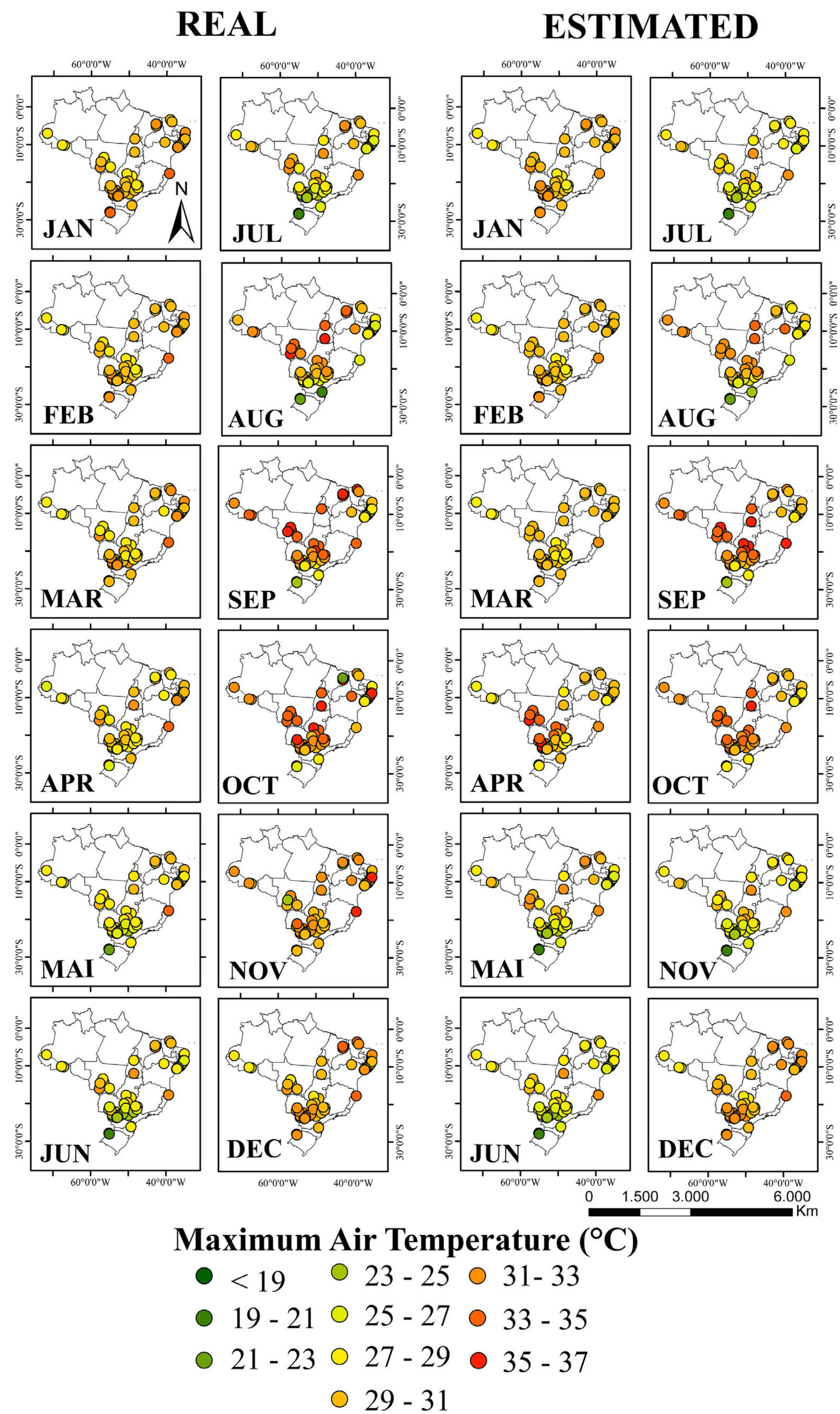

Figure 7 - Spatialization of the estimated maximum air temperature in Brazil for each month of the year.

April, August, and October showed the lowest accuracy, with MAPE values of 5.14% ± 7.18, 4.17% ± 3.04, and 3.71% ± 3.07, respectively (Fig 5E, H, J).

The models calibrated for December performed better in the Southeast (MAPE = 0.85% and R2adj = 0.92) and Midwest (MAPE = 1.72% and R2adj = 0.80). Bardin *et al*. (2010) found similar values for the Southeast region, with higher R2adj values also in December. October had the highest Tmax values for the North and Southeast and showed the best accuracies, with MAPE values of 1.31 and 1.22%, respectively (Fig. 5F, G, H, I, J).

The spatial variation of the predicted *Tmin* is shown in Fig. 6. In the South, the actual *Tmin* varied from 9 to 24 °C over the year, demonstrating its aptitude for sugarcane cultivation (Gouvêa *et al*., 2009). Moreover, the Midwest region showed *Tmin* values above 13 °C, as observed in the municipalities of Rio Brilhante (MS), Itumbiara (GO), and Cáceres (MT) (Fig. 6). With high accuracy, the regressive models could predict all the temporal variation of minimum temperatures for the sugarcane regions in the Midwest (Fig. 6).

A relatively low deviation was observed between the actual and the estimated *Tmin* in all locations over the year, with an average of 0.029 ± 0.13 (Fig. 8). June to September showed the highest deviations between locations, with a difference of up to −3.5 and 2 °C. The locations in the North region showed the highest deviations, with an annual average of 0.15 ± 0.45 °C, with a wide variation between the months of the year. The municipalities in the South region of Brazil, on the other hand, had the lowest deviations, with an annual average of 0.018 ± 0.13 °C, with the municipalities of Roque Gonzales, Porecatu, and Paranacity presenting the lowest values (Fig. 8). These three municipalities have an expressive sugarcane production, reaching values of 0.33, 0.833, and 1 million tons, respectively (IBGE 2018). Thus, the models can assist in monitoring the phenological crop stages and in the decision making (Dos Santos Almeida *et al*., 2008).

The actual and estimated annual average *Tmax* in sugarcane regions was 29.48 ± 1.62 °C and 29.60 ± 1.67 °C, respectively (Fig. 7). October presented the highest *Tmax* and estimated *Tmax*, with annual averages of 31, 47, and 31.50 °C, respectively. The municipalities of the Midwest region had the highest *Tmax*, with an annual average of 30.33 ± 1.9 °C, standing out the municipalities of Diamantina (MT), Aparecida do Taboado (MS), and Sidrolândia (MS) (Fig. 7).

The difference between *Tmax* and estimated *Tmax* is shown in Fig. 8. The annual average deviation of all locations was −0.12 ± 0.35 °C, with April showing the highest variation between Tmax and the estimated Tmax, with a value of −1.19 °C, and July with the lowest average value (−0.002 °C). The highest deviations occurred in locations of the Midwest region, with an average of −0.52 ± 1.30 °C, while the lowest deviations were found in municipalities of the North region, with an average of −0.19 ± 0.72 °C. In this case, Plácido de Castro (AC) presented the lowest deviation among all locations, with an average value of 0.001 °C (Fig. 8). This municipality has undergone several changes in its soil cover in recent years (Delgado *et al*., 2012). Therefore, the model calibrated for the region could assist in the choice of species for its reforestation (Hobbs *et al*., 2016).

Regarding the Maximum Air Temperature, a clear separation of the locations into three groups (clusters) was observed (Fig. 9). The green group presented the lowest temperatures, being formed by Japoatã (SE) and Campo Alegre (AL), with an average of 22.78 ± 0.24 ºC. The red group had medium temperatures, formed by 50 cities, such as Pacatuba (SE), Jaboticabal (SP) and Porto Xavier (RS), with an average of 29.18 ± 0.92 ºC. On the other hand, the blue group showed the highest maximum air temperatures, with an average of 32.29 ± 0.85 ºC, formed by 8 cities, such as Presidente Kennedy (ES), Rio Brilhante (MS) and Juazeiro (BA).

On the other hand, for the minimum air temperature values, there was a separation of the studied localities into two groups (clusters) (Fig. 10). The Red cluster presented the lowest minimum temperature values, with an average of 17.90 ± 1.66 °C, being formed by 33 cities, such as Campo Alegre (AL), Roque Gonzales (RS) and Sidrolândia (MS). The green group presents higher minimum temperature values, having an average of 22.92 ± 0.91 °C, with 27 cities in the group, such as Paracuru (CE), Laranjeiras (SE) and Porecatu (PR).

The variation between the actual and estimated values of maximum and minimum air temperature showed some months with larger errors (Fig. 11). For maximum air temperature, the average deviation was 0.033 ± 1.87, with values ranging from −7.77 to 8.87 (Fig. 11A). August was the month with the largest deviations, with −0.120 ± 3.37, while December showed the smallest deviations, with an average of -0.004 ± 1.46. As for the minimum air temperature, the average deviation was 0.65 ± 2.43, ranging from -6.28 to 8.96 (Fig. 11B). January was the month with the largest deviations, with an average of 5.459 ± 2.44 and February was the month with the smallest deviations, with an average of 0.306 ± 1.02. Thus, the period that showed the lowest deviations from the actual and estimated air temperature was December to April, with a greater deviation during winter, from June to September.

4. Final Considerations

It is possible to estimate *Tmax* and *Tmin* as a function of the coordinates and altitudes for the entire Brazilian territory. The MAPE and R2 values showed accuracy and precision in the models for the estimated maximum

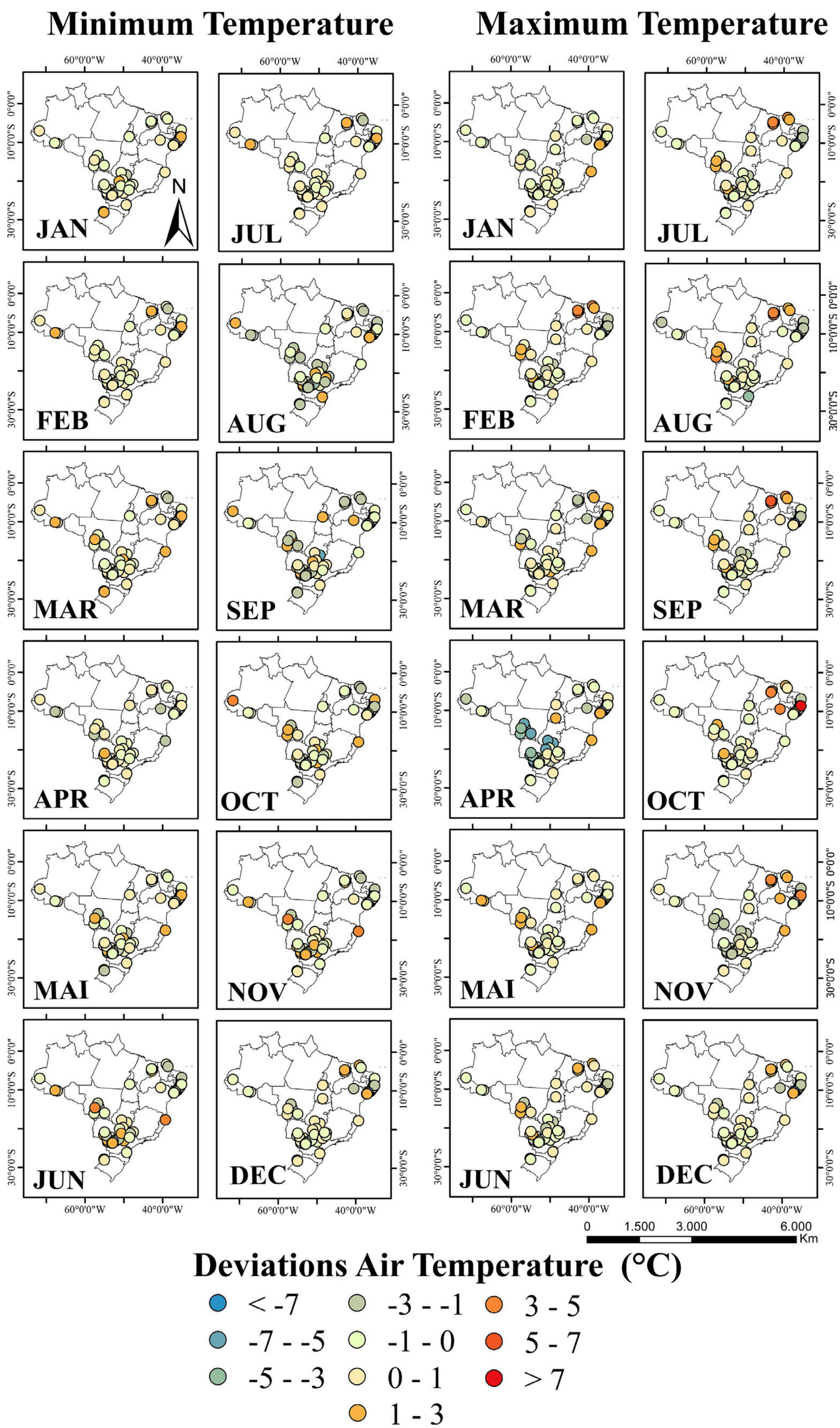

Figure 8 - Spatialization of the deviation between estimated and actual maximum and minimum air temperature in Brazil.

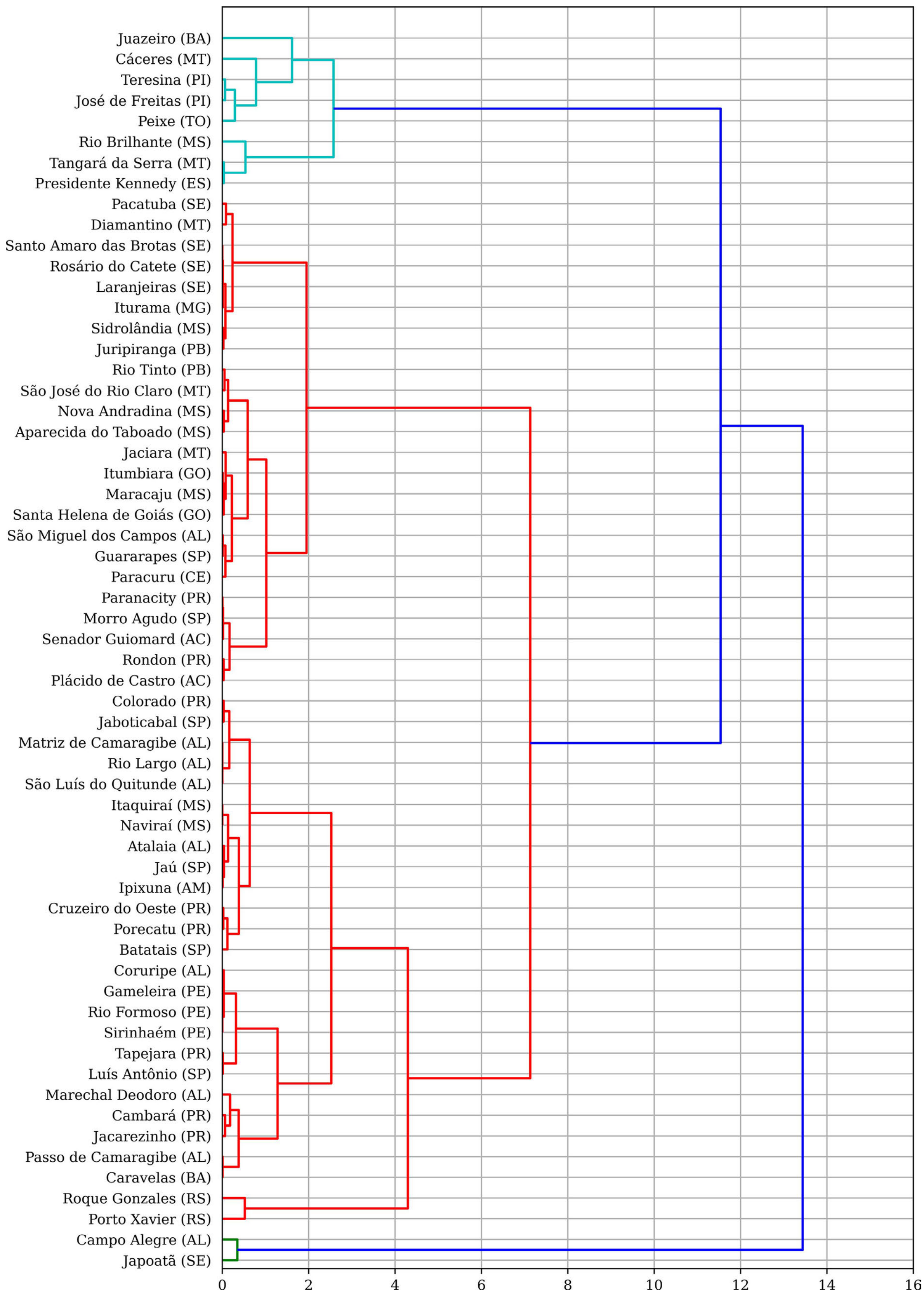

Figure 9 - Dendrogram for the identification of maximum temperature groups of the largest sugarcane producing locations.

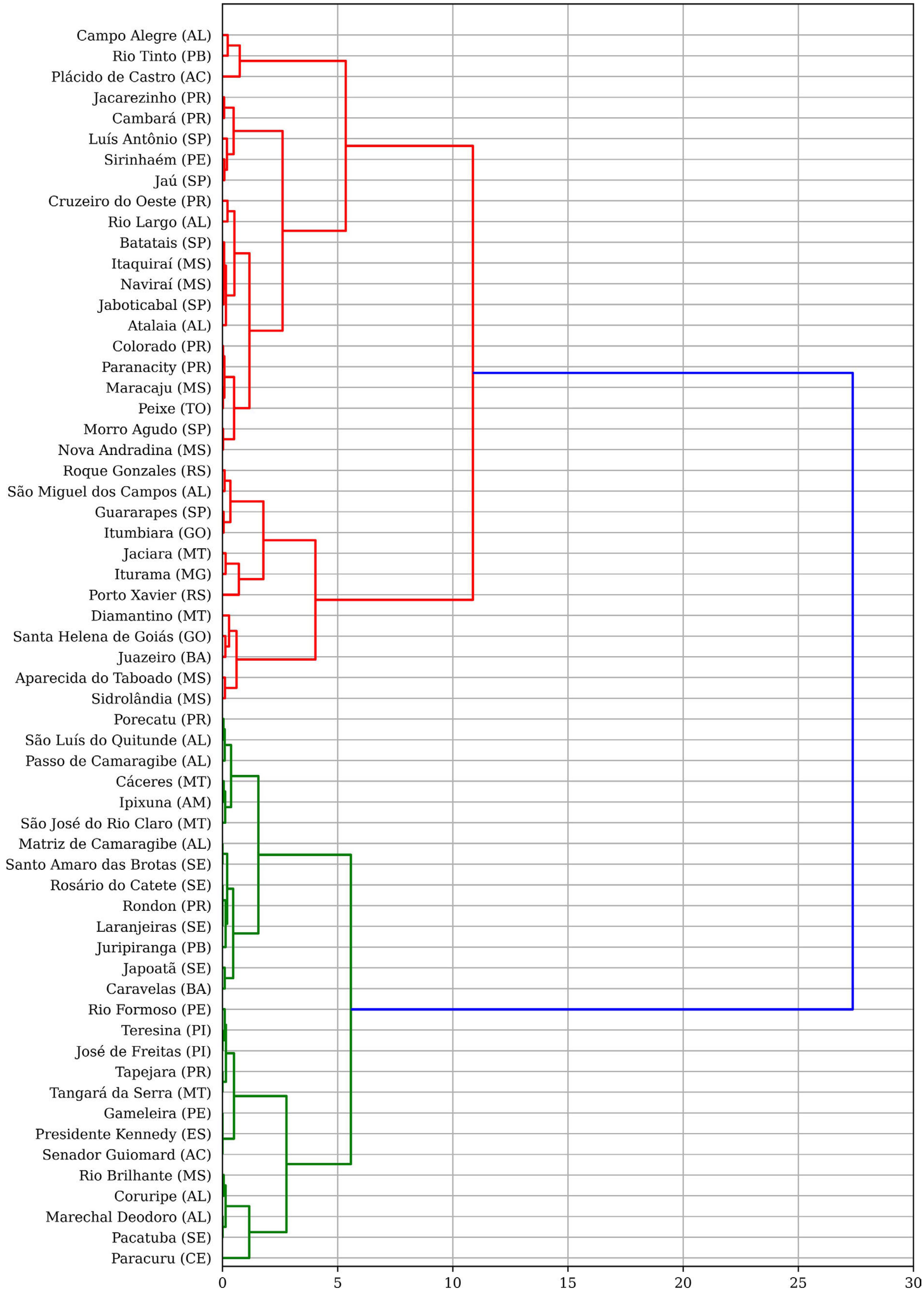

Figure 10 - Dendrogram for the identification of minimum temperature groups of the largest sugarcane producing locations.

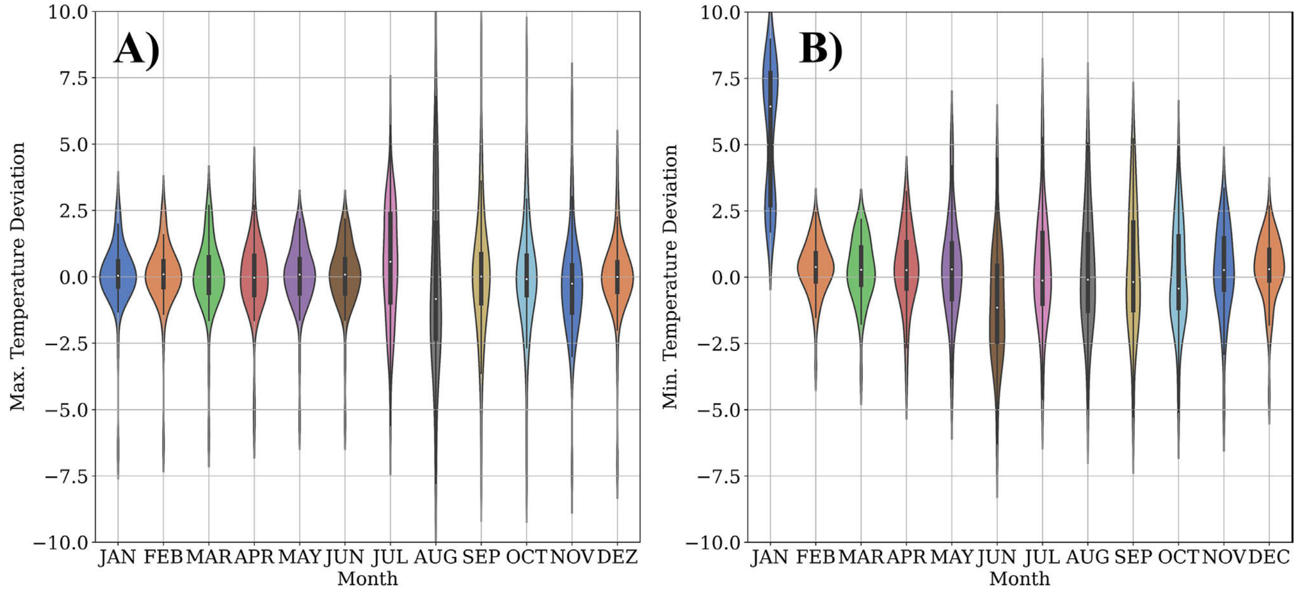

Figure 11 - Monthly variation of the deviations between estimated and actual temperature, where A) Maximum Temperature and B) Minimum Temperature.

and minimum temperatures, indicating that the equations can be used to estimate the temperatures in sugarcane areas.

The models for estimating maximum temperature demonstrate precision between 0.40 and 0.9, whereas the minimum temperature varied from 0.57 to 0.98. The lowest MAPE values of the models for the estimation of minimum air temperatures are 0.76, 0.97, and 1.21%, occurring in the North and Southeast in February, March, and January, respectively.

The lowest MAPE values for the estimation models of the maximum air temperature are 0.74, 0.75, and 0.80% for locations in the Southeast region in February, January, and April, respectively. January, February, and March have the highest accuracy for *Tmax* and *Tmin*.

The *Tmin* estimation model for the Southeast region in July shows the best performance, with a MAPE value of 1.28 and an R2adj of 0.94. The *Tmax* model of the North region for September presents higher precision and accuracy, with values of 1.28 and 0.96, respectively.

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