



## EARTH SCIENCES

# Spatial-temporal variability of rainfall and mean air temperature for the state of Bahia, Brazil

CAIQUE C. MEDAUAR, SAMUEL A. SILVA, LUIS CARLOS C. CARVALHO, ÍCARO M. GALVÃO & PHILYPE V. MACEDO

**Abstract:** The aim of this study was to evaluate spatial behavior and temporal stability of rainfall and mean air temperature in the state of Bahia, using historical series from 1975 to 2011 and 1961 to 2009, respectively. The analyses were performed considering the accumulated variables of each month of the historical series. The accumulated monthly totals were divided by the number of years of observation, obtaining the monthly average values of rainfall and air temperature for each measurement point. The data were submitted to descriptive statistical analysis and linear correlation studies. Geostatistical analysis was used to verify the existence and quantify spatial dependence between the values of the studied variables. In addition, the maps were submitted to algebra operations, calculating the spatial difference between months for each of the variables. For that purpose, the difference between one month and its subsequent period was calculated in order to establish the behavior of the variables over time. Climatic variables showed a close relationship between each other, demonstrating their spatial and temporal variation, which is mainly dependent on the seasons of the year. The rainfall and mean air temperature variables showed stable spatial behavior and high temporal stability between subsequent months.

**Key words:** climatic variables, geostatistics, meteorology, thematic maps.

## INTRODUCTION

Agricultural and socio-environmental planning are related to specific climatic conditions in order to be carried out effectively. An example of this relationship are the adversities of long periods of drought and high temperatures, influenced by climatic and oceanic phenomena such as El Niño (Hastenrath 2012). In the midst of these events, many research has been conducted over the years in several Brazilian states, with the aim of monitoring and evaluating environmental variables more precisely and analyzing climatic conditions, as well as their spatial and/or temporal variations, as described by Sartori et al. (2010), Santos et al. (2011) and Silva & Lima

(2011) for the states of São Paulo, Goiás and Espírito Santo, respectively.

Applications of statistical models, such as geostatistics, have sought to explain the behavior of meteorological and climatic phenomena occurring in nature (Sartori et al. 2010). In data analysis developed through classical statistics, random variables are considered independent of each other, thus disregarding the influence between neighboring observations. However, rainfall and mean air temperature present structure in their neighboring variations, which characterizes spatial dependence of the data in different periods of the year, providing a more accurate estimate of the variable of interest through geostatistics (Santos et al. 2011).

Silva et al. (2012) state that systems that can reliably analyze information on the climatology of a region are of fundamental importance; especially for socio-environmental management and agricultural practices. In addition, Silva et al. (2010) report that decisions made regarding conditions of climatic variables are relevant for agricultural management and, in certain situations, can assure the success of a venture. Thus, knowledge of the spatial-temporal variation of rainfall and mean air temperature based on a historical series may be an essential predictor of these phenomena in a specific region (Detzel et al. 2016).

High spatial variability of climatic variables is expected in extensive areas such as the state of Bahia, especially when considering the heterogeneous landscape and the factors controlling the tropical climates. Likewise, due to seasonality, some climatic variables can present a distinct behavior along a given macro-region, requiring singular and segmented interpretations of the different realities.

In accordance with what has been demonstrated, this study aimed to evaluate the spatial behavior and temporal stability of rainfall and mean air temperature in the state of Bahia.

## **MATERIAL AND METHODS**

The state of Bahia is located in the south of the northeastern region of Brazil and has an area of 564,732,642 km<sup>2</sup>, with about 69.31% of its territory being located in the Brazilian semi-arid region. According to the Köppen classification, the climate (Alvares et al. 2013) is Af, Aw and BSh types, being tropical humid, tropical with dry winter season and hot arid, respectively. Annual cumulative rainfall exceeds 1,600 mm on the coast and 400 mm in the northern end of

the state and mean annual air temperatures are high, with a maximum of 30 °C.

For this study, climatic variables of rainfall and mean air temperature were used. For rainfall, 36-year historical series data were used from the period between 1975 and 2011. Mean air temperature data refer to the historical means in the period between 1961 and 2009, available in grid format with cells of 10' x 10' latitude and longitude (New et al. 2002). To complement the data series of these variables, daily data on average monthly temperature from historical series of the Instituto Nacional de Meteorologia (INMET) were also used. In addition, information obtained from 519 measurement points distributed throughout the territory of Bahia was used, adding the stations of the Agência Nacional de Águas (ANA) to INMET data and data from the Unidade de Pesquisa Climática (UPC).

The analyses were performed considering the accumulated variables of each month of the historical series. The accumulated monthly totals were divided by the number of years of observation, obtaining the monthly average values of rainfall and air temperature for each measurement point.

The results were submitted to descriptive statistical analysis to determine the position measurements (mean and median), dispersion (coefficient of variation) and dispersion shape (asymmetry and kurtosis coefficients). In order to verify temporal stability over the months, Pearson's linear correlation analysis was performed for each variable at a 5% probability level.

Subsequently, a geostatistical analysis was performed in order to verify the existence of and quantify the degree of spatial dependence between values of the variables studied, through the adjustment of theoretical functions to the models of classical experimental variograms based on the assumption of the hypothesis

of intrinsic stationarity, as per equation 1 (Matheron 1963):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i+h)]^2 \quad (1)$$

Where:  $N(h)$  is the number of  $[Z(x_i), Z(x_i+h)]$  pair of values separated by an  $h$ -vector and  $x_i$  is a spatial position of variable  $Z$ , which corresponds to the monthly mean value of the variable.

In the segment of adjustments of theoretical functions to the experimental variograms, several models were tested; linear with baseline, gaussian, exponential and spherical. In the choice of models, the criterion of least squares was used, selecting the models with the highest  $R^2$  (coefficient of determination) value, lowest SQR (squared sum of the residuals) and highest correlation coefficient value of the cross-validation.

For analysis of the spatial dependence index (SDI), the relationship between the nugget effect and the threshold,  $C_0/(C_0 + C)$ , was used, with the intervals proposed by Cambardella et al. (1994), which consider strong (SDI <25%); moderate ( $25\% \leq SD < 75\%$ ) and weak ( $SD \geq 75\%$ ) spatial dependence. After proving spatial dependence, the geostatistical interpolation ordinary kriging method was used to estimate values at unmeasured locations. This method has been widely used in studies on spatial distribution of climatic variables for data interpolation in non-sampled locations (Almeida et al. 2017).

Additionally, the maps were submitted to algebra operations, calculating the spatial difference between months for each of the variables used in the study. For this, the difference between month  $n$  and month  $n-1$  was calculated, in order to establish the behavior of the variables over time and to highlight areas where temporal stability was greater, smaller and/or nonexistent.

## RESULTS AND DISCUSSION

The results of the descriptive statistical analysis of the variables of rainfall and mean air temperature for the state of Bahia are presented in Table I.

The values of the central tendency (mean and median) measurements of the monthly means were very close, especially for mean air temperature, indicating symmetrical distributions. This is confirmed by the skewness value close to zero.

All data presented leptokurtic distribution, with the exception of mean air temperature in May, September, October, November and December (mesokurtic distribution). Sartori et al. (2010) verified a distinct result for temperature in a study of temporal variability in the state of São Paulo, in which it was possible to observe a platykurtic distribution, that is, a kurtosis coefficient smaller than zero.

The coefficient of variation (CV), according to the classification proposed by Warrick & Nilsen (1980), low for  $CV < 12\%$ , medium of  $12\% < CV < 60\%$ , and high for  $CV > 60\%$ , was low for mean air temperature and medium for rainfall, with the highest values for the months from August to November and from June to August, respectively. These results indicate a homogeneous distribution of the variables over the course of the months, especially for temperature, of which the low variability can be attributed to the stable behavior of the hot and cold air masses in the seasons/months in the state of Bahia.

Sartori et al. (2010), evaluating the variability of climatic data in Botucatu-SP, found CV values for temperature classified as medium to low variation. Silva et al. (2003), working with data from Uberaba-MG, verified that the precipitation presented medium to high CV and stated that the total absence of rainfall in some years of

**Table I. Monthly descriptive statistics of rainfall and mean air temperature in the state of Bahia.**

Month	Mean	Median	CV (%)	Cs	Ck
<b>Rainfall<sup>1</sup></b>					
Jan	167.9	155.8	32.70	2.34	11.41
Feb	176.5	164.5	32.66	2.06	9.76
Mar	171.6	160.1	31.68	2.33	13.06
Apr	144.9	134.3	27.88	4.02	35.12
May	138.3	119.6	35.96	3.24	12.25
Jun	157.2	126.1	49.17	2.96	10.20
Jul	176.8	144.1	52.58	2.69	8.33
Aug	158.9	131.3	51.95	3.27	12.31
Sep	143.0	119.6	37.73	3.17	13.32
Oct	169.1	144.1	41.72	2.09	8.17
Nov	167.3	140.7	46.06	3.54	24.74
Dec	157.6	140.7	34.86	3.27	21.54
<b>Mean air temperature<sup>2</sup></b>					
Jan	25.0	25.3	6.56	-0.83	1.32
Feb	25.3	25.6	6.20	-0.83	1.26
Mar	25.2	25.5	6.29	-0.89	1.39
Apr	24.3	24.6	6.56	-0.74	1.07
May	22.7	23.0	7.34	-0.58	0.70
Jun	21.6	21.9	7.46	-0.82	1.13
Jul	21.1	21.3	7.60	-0.84	1.32
Aug	21.7	21.8	7.84	-0.78	1.28
Sep	23.3	23.2	7.99	-0.55	0.87
Oct	24.8	24.7	7.71	-0.34	0.51
Nov	24.7	24.8	7.82	-0.07	0.53
Dec	24.6	24.8	7.14	-0.54	0.76

<sup>1</sup> - Dimensionless; <sup>2</sup> - °C; Jan – January; Feb – February; Mar – March; Apr – April; Jun – June; Jul – July; Aug – August; Sep – September; Oct – October; Nov – November; Dec – December; CV - Coefficient of variation; Cs - Coefficient of skewness; Ck - Coefficient of kurtosis.

the series in the dry season may explain this variability. The results of the present study for rainfall are in accordance with the work of Lima et al. (2016) who evaluated mean monthly precipitation in the state of Espírito Santo and found that the highest CV values are also between June and August.

The results of the Pearson correlation analysis between the monthly averages of the variables studied are presented in Table II. Taking into consideration subsequent months, all monthly rainfall means and mean air temperature showed a significant correlation, which indicates stable spatial behavior over time.

This behavior may be associated with low and medium variability for temperature and rainfall, respectively (Table I). These results imply high temporal stability, proving that there is low variability between periods in the same season and/or interval of months between seasons in the state of Bahia.

Nevertheless, when evaluating the behavior of the variables between months of different seasons of the year, it is possible to observe differences between the monthly means. For rainfall, the month of June (winter) presented a negative correlation when correlated with the months of January, February and March (summer), that is, a behavior of low spatial

**Table II. Pearson linear correlation of the mean monthly rainfall and mean air temperature in the state of Bahia.**

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
<b>Rainfall</b>												
<b>Jan</b>	1.00	0.98	0.96	0.90	0.11	-0.21	-0.26	-0.17	0.17	0.66	0.93	0.97
<b>Feb</b>		1.00	0.98	0.83	-0.04*	-0.34	-0.38	-0.29	0.03*	0.59	0.88	0.93
<b>Mar</b>			1.00	0.83	0.00*	-0.28	-0.32	-0.25	0.01*	0.51	0.82	0.92
<b>Apr</b>				1.00	0.49	0.15	0.08*	0.16	0.48	0.72	0.90	0.94
<b>May</b>					1.00	0.92	0.88	0.86	0.79	0.24	0.23	0.27
<b>Jun</b>						1.00	0.99	0.96	0.70	-0.07*	-0.11	-0.04*
<b>Jul</b>							1.00	0.97	0.65	-0.16	-0.17	-0.09*
<b>Aug</b>								1.00	0.76	-0.07*	-0.10	-0.03*
<b>Sep</b>									1.00	0.56	0.31	0.25
<b>Oct</b>										1.00	0.80	0.63
<b>Nov</b>											1.00	0.93
<b>Dec</b>												1.00
<b>Mean air temperature</b>												
<b>Jan</b>	1.00	0.99	0.97	0.97	0.80	0.39	-0.01*	0.19	0.50	0.71	0.94	0.99
<b>Feb</b>		1.00	0.98	0.96	0.76	0.34	-0.07*	0.13	0.43	0.66	0.91	0.98
<b>Mar</b>			1.00	0.93	0.70	0.29	-0.10	0.07*	0.36	0.59	0.84	0.96
<b>Apr</b>				1.00	0.90	0.52	0.12	0.34	0.60	0.78	0.94	0.96
<b>May</b>					1.00	0.80	0.46	0.64	0.73	0.80	0.89	0.81
<b>Jun</b>						1.00	0.89	0.86	0.56	0.49	0.54	0.44
<b>Jul</b>							1.00	0.84	0.33	0.18	0.17	0.05*
<b>Aug</b>								1.00	0.76	0.60	0.39	0.21
<b>Sep</b>									1.00	0.95	0.65	0.46
<b>Oct</b>										1.00	0.82	0.67
<b>Nov</b>											1.00	0.94
<b>Dec</b>												1.00

Jan – January; Feb – February; Mar – March; Apr – April; Jun – June; Jul – July; Aug – August; Sep – September; Oct – October; Nov – November; Dec – December; \* - Not significant at 5% probability level.

**Table III. Models and parameters of the medium variograms adjusted for mean monthly rainfall and mean air temperature in the state of Bahia.**

Month	Model	$C_0$	$C_0+C$	A (km)	SDI (%)	$R^2$	$R^2(VC)$
<b>Rainfall</b>							
Jan	Sph	0.15	0.90	394	16.8	99.3	57.9
Feb	Sph	0.31	0.91	386	33.7	97.2	64.3
Mar	Exp	0.29	0.93	353	31.2	96.8	57.2
Apr	Exp	0.32	1.03	317	31.6	97.5	59.5
May	Exp	0.31	1.27	231	24.3	95.1	67.2
Jun	Exp	0.18	1.21	209	14.7	96	65.8
Jul	Exp	0.08	1.22	195	6.6	96.5	56.7
Aug	Sph	0.02	1.10	90	2.2	99.1	58.4
Sep	Sph	0.04	1.09	85	3.4	98.4	53.5
Oct	Gau	0.35	1.56	680	22.4	98.8	69.2
Nov	Sph	0.21	1.73	860	12.1	97.9	69.8
Dec	Gau	0.52	2.23	1020	23.1	93.7	77.2
<b>Mean air temperature</b>							
Jan	Sph	0.25	1.19	540	21.0	97.7	61.2
Feb	Sph	0.19	0.95	362	20.0	97.1	60.4
Mar	Exp	0.23	1.23	490	18.7	97.2	56.3
Apr	Sph	0.22	1.05	383	21.0	98.2	55.3
May	Sph	0.19	1.13	390	16.8	98.7	59.3
Jun	Exp	0.26	1.11	315	23.3	95.4	58.7
Jul	Sph	0.28	1.03	269	26.8	71.6	54.2
Aug	Sph	0.33	1.09	357	30.1	93.8	67.8
Sep	Sph	0.30	1.24	560	24.6	99.5	68.3
Oct	Sph	0.30	1.19	506	25.5	93.9	60.2
Nov	Sph	0.28	1.42	737	19.6	99.8	51.5
Dec	Exp	0.32	1.50	1113	21.7	97.7	71.2

**Jan – January; Feb – February; Mar – March; Apr – April; Jun – June; Jul – July; Aug – August; Sep – September; Oct – October; Nov – November; Dec – December;  $C_0$  – Nugget effect;  $C_0+C$  – Sill; A – range; SDI – Spatial dependency index;  $R^2$  – Coefficient of determination of the model;  $R^2(VC)$  – Coefficient of cross validation determination; Exp – Exponential; Sph – Spherical; Gau – Gaussian.**

continuity and temporal stability. This result is associated with non-seasonality of the phenomenon, that is, the state of Bahia does not have clearly defined seasons. This may be seen in the central-eastern region of Bahia, which despite maintaining average temperatures that

can vary between 25 and 26 °C throughout the year, has the highest precipitation index in winter. Tanajura et al. (2010) state that in part of the semi-arid region of Bahia, the behavior is different from that described previously, which, even though it has a dry climate throughout the

year, the small distribution of rainfall usually occurs in the summer.

For mean air temperature, the month of July (winter) did not present a significant correlation when correlated with the months of January and February (summer), indicating that the behavior between these months is independent. When this behavior is demonstrated in a historical series, there is an indication that, in a certain period of evaluation, the distribution of the phenomenon is discontinuous, avoiding an expected pattern.

Behavior of temporal discontinuity in historical series of climatic data may be associated with the influence of atypical years in the distribution (when these are not removed from the database) and/or a natural condition of the phenomenon under study. When this second condition is predominant, special attention must be paid to these periods/months in any social, economic or environmental planning.

In the geostatistical analysis (Table III), the studied variables presented spatial dependence in all months of evaluation, indicating that the distribution in the area is not random, but depends on the distance separating the samples. Mello et al. (2012), evaluating the spatial distribution of monthly and annual precipitation for the state of Espírito Santo, verified that all months of the year also presented spatial dependence.

For rainfall, the theoretical models that best fit the experimental variograms were spherical (41.7%), exponential (41.7%) and Gaussian (16.6%). The mean air temperature data fit only the spherical (75%) and exponential (25%) models. The adjusted variograms showed well defined levels ( $C_0+C$ ), which indicates that the hypothesis of intrinsic stationarity was met and that the variables do not present a trend of variation with direction (Isaaks & Srivastava 1989).

Most of the monthly means of the variables presented a strong spatial dependence, analyzed

by the spatial dependency index (SDI) and in accordance with the classification proposed by Cambardella et al. (1994), except for the monthly means for February, March and April (rainfall) and July, August and October (mean air temperature), which presented moderate spatial dependence. The existence of spatial dependence is fundamental in geostatistics for the elaboration of maps through high-precision kriging (Vieira 2000).

The range value of the variograms for rainfall and mean air temperature ranged from 85 km (September) to 1020 km (December) and 269 km (July) to 1113 km (December), respectively. The high value of (a) presented by the variables in the month of December proves that within this interval the variable presents low spatial variability, since its area of influence will be greater, suggesting greater similarity between the neighboring points, that is, implying behavior of high spatial continuity. Mello et al. (2012), after evaluating the spatial distribution of monthly rainfall in the state of Espírito Santo, verified that the highest range values were also for the month of December.

Range is an important parameter of the variogram that has practical interpretations, since it indicates the distance between two points in which there is spatial dependence (Almeida et al. 2017). According to these same authors, high range values are associated with high temporal stability and, together with the good fit of the experimental variograms, directly influence the kriging estimation, since the estimation of values in non-sampled places is more reliable and better represents the variable in the study area.

Based on the semivariance models and considering the adjusted parameters, rainfall and mean air temperature data were interpolated using ordinary kriging.

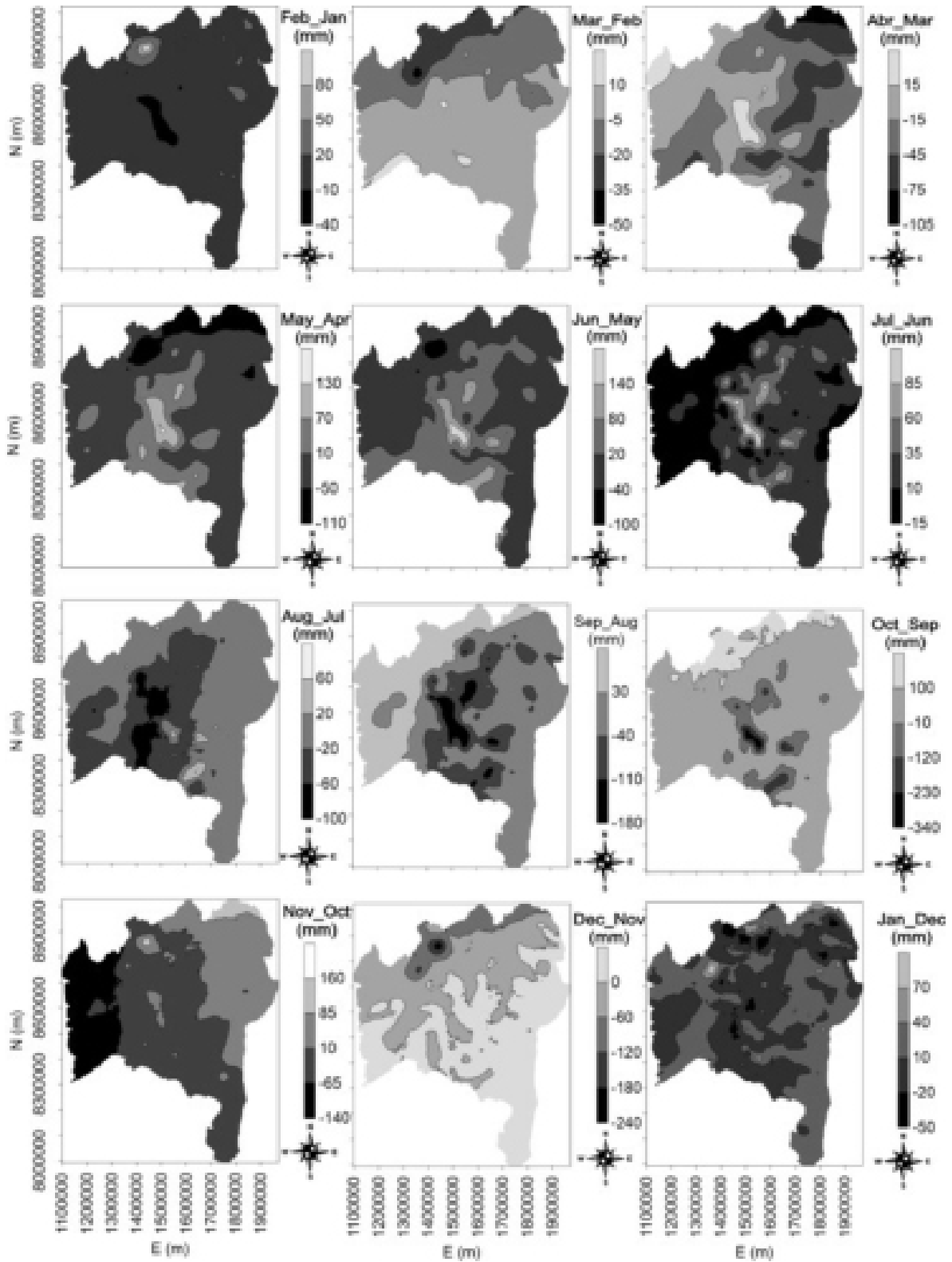


Figure 1. Thematic maps of the month-to-month temporal evolution of rainfall for the state of Bahia.



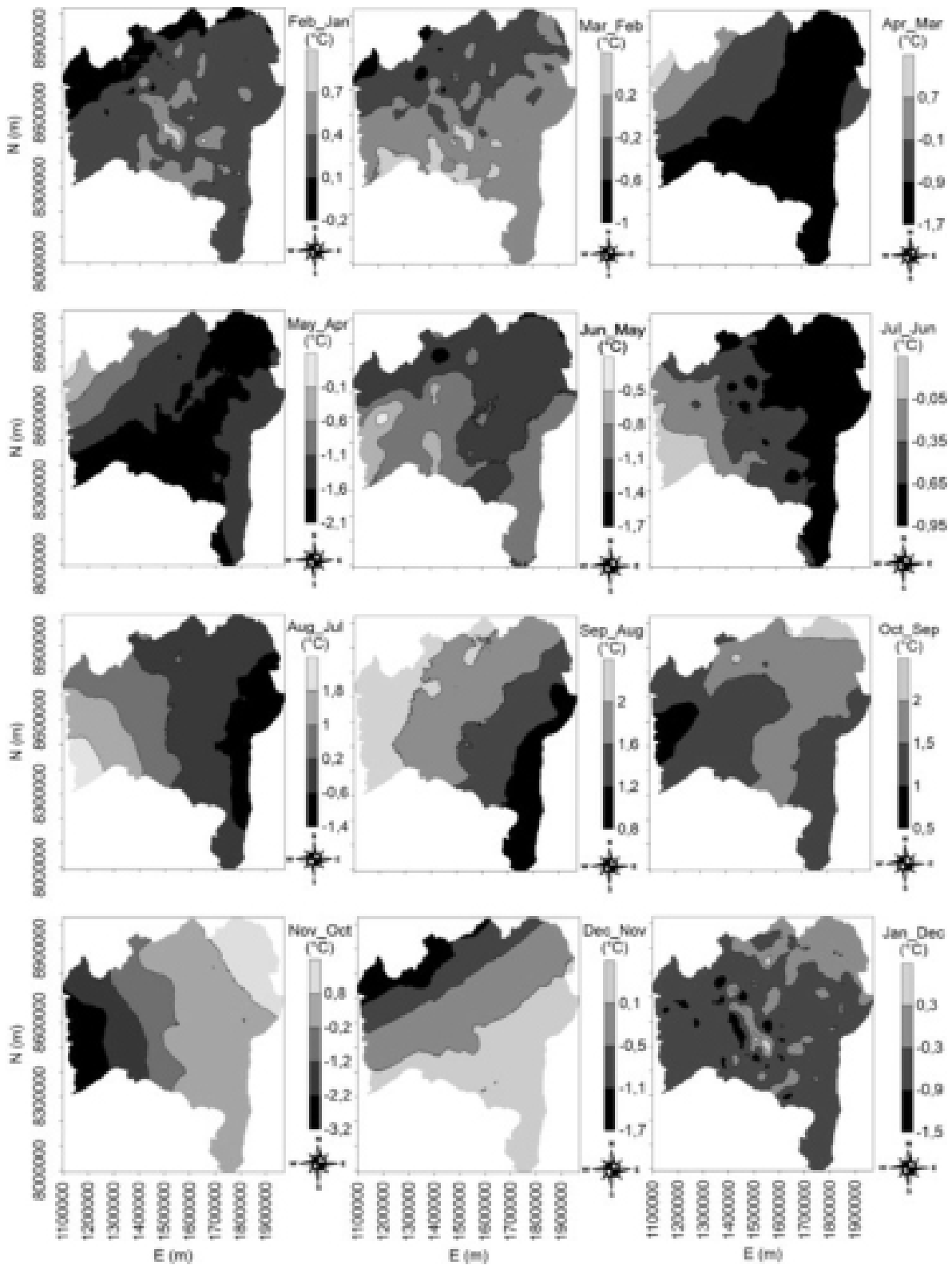


Figure 2. Thematic maps of the month-to-month temporal evolution of mean air temperature for the state of Bahia.

Analyzing the thematic maps of rainfall (Figure 1) constructed through kriging, it can be observed that the lowest indices of variability occur in the southern region, part of the northern region and a large part of the coastal region, mainly in the temporal evolution of the summer months, where the rainfall distribution is more homogeneous, implying greater temporal stability.

On the other hand, it can be observed that the greatest variability occurs mainly in the central region of Bahia, with semi-arid characteristics, and part of the western region, where the Bahia cerrado prevails. This occurs mainly in the temporal evolution of the months of September/August and November/October, respectively, and may provide lower water availability in the soil during some of these periods, rendering the implementation of some agricultural practices impracticable. The different atmospheric circulation systems that operate in these regions make the climatology complex, which reflects in great climatic variability, especially in relation to rainfall, with precipitation events that vary in time and space (Almeida et al. 2017). Chapada Diamantina, in the central region of the state, represents the orographic effect more expressively, providing a local semi-arid climate with high annual rainfall variation, above 1,000 mm (Tanajura et al. 2010).

The rainfall variation is due to the conjunction of different meteorological systems, such as the Intertropical Convergence Zone (ZCIT), that operate in the state of Bahia, the Upper Tropospheric Cyclonic Circulation Systems (UTCS), the Polar Atlantic Front (PAF), the South Atlantic Convergence Zone (NACS) (Nunes et al. 2016), sea/land breezes, winds, and a relief consisting of plains, valleys, sierras and mountains. Variations in the spatial-temporal distribution of rainfall, associated with low annual rainfall regimes in the largest portion of the state, have a

direct impact on rainfed agriculture. Knowledge of this agrometeorological variable could guide decision making for agricultural management, as in the study of zoning, crop forecasting and climatological characterization, since the high variation of pluviometers can lead to gross planning errors, causing serious losses due to high water deficits that may occur and are not predicted in studies (Silva & Lima 2011).

Analyzing the month-to-month temporal evolution of mean air temperature (Figure 2), it can be observed that the variations between all the months are low. The greatest difference is observed between the months of November/October, with a reduction in temperature ranging from 2.2 to 3.2 °C, which can be visualized by the black coloring that covers part of the western region of Bahia.

The biggest variation in temperature found for the western region between the months of November/October has a close relationship with the rainfall between the same periods (Figure 1). These results demonstrate that thermal variation is also influenced by the rainfall regime in western Bahia, thus allowing such information to aid in the decision making of agricultural and environmental planning regarding the beginning of the harvest, which occurs in this period for the annual planted crops of the rainfed region.

For the other periods, geographical factors such as large water bodies (oceans) act as a thermal regulator of temperature, tending to soften fluctuations and reduce the monthly variability of this variable (Varejão 2006). These results of low variability and high temporal stability were expected, since most of the state presents a tropical climate and does not have temperature discrepancies.

Climate change and increasing weather events, especially in terms of air temperature and rainfall, have been a cause for concern for government authorities, as well as all segments

of society. Every year, millions of people are affected by climate change and natural disasters causing great damage to socioeconomic and environmental sectors (Andrade et al. 2018), such as food security, which involves everything from the farmer's ability to produce, to stability of supply and nutritional quality of the food (Savary et al. 2017).

The generation of information on rainfall and air temperature is extremely relevant, since these are key factors in several scenarios, such as agricultural and environmental planning, water erosion, environmental risk assessment, irrigation production, planning and management. Melo Junior et al. (2006) stated that in the last decade, climate change and the consequences of global warming have become the focus of much of the scientific population's challenges linked to plant production, since the metabolic processes of plants are directly affected by meteorological factors. In addition, the climate exerts a great influence on the relationship of plants with insects and microorganisms, favoring or not the incidence of pests and diseases, besides influencing the metabolic activities that can affect the growth, development and productivity of crops (Taiz & Zeiger 2013).

In general terms, the climatic parameters evaluated are closely related to each other, demonstrating their spatial and temporal variation, which is mainly dependent on the seasons of the year. In the state of Bahia, the seasons of the year are not well defined as in the southern states of Brazil, which indicates a trend of reduced variation of the variables over the years, demonstrating high temporal stability.

## CONCLUSIONS

Rainfall and mean air temperature variables show stable spatial behavior and high temporal stability between subsequent months.

Spatial dependence was observed in all months of evaluation for the two variables under study.

The application of the geostatistical tool enabled the generation of thematic maps based on the spatial distribution of the variables, identifying where there was greater and lesser temporal variability between subsequent months for the state of Bahia.

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#### CAIQUE C. MEDAUAR<sup>1</sup>

<http://orcid.org/0000-0001-8339-5244>

#### SAMUEL A. SILVA<sup>2</sup>

<http://orcid.org/0000-0002-0718-7328>

#### LUIS CARLOS C. CARVALHO<sup>1</sup>

<http://orcid.org/0000-0002-2790-3723>

#### ÍCARO M. GALVÃO<sup>3</sup>

<http://orcid.org/0000-0002-8498-4742>

#### PHILYPE V. MACÊDO<sup>1</sup>

<https://orcid.org/0000-0002-1884-272X>

<sup>1</sup>Departamento de Ciências Agrárias e Ambientais, Universidade Estadual de Santa Cruz, Rod. Jorge Amado, Km 16, Salobrinho, 45662-900 Ilhéus, BA, Brazil

<sup>2</sup>Departamento de Engenharia Rural, Universidade Federal do Espírito Santo, Alto Universitário, s/n, Guararema, 29500-000 Alegre, ES, Brazil

<sup>3</sup>Departamento de Engenharia de Biosistemas, Escola Superior de Agricultura Luiz de Queiroz/Universidade de São Paulo, Av. Pádua Dias, 11, Agronomia, 13418-900 Piracicaba, SP, Brazil

Correspondence to: **Caique Carvalho Medauar**

*E-mail: caiquemedauar@hotmail.com*

### **Author contributions**

The authors Caique C. Medauar, Samuel de A. Silva and Phylipe V. de Macêdo are responsible for the development and execution of the research, as well as for the writing of the article. The authors Luis C. C. Carvalho and Ícaro M. Galvão also helped in the writing of the manuscript, however they were more prominent in revising it.

