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RAINFALL ZONING FOR COCOA GROWING IN BAHIA STATE (BRAZIL) USING FUZZY LOGIC

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KEYWORDS

Land suitability; mapping; spatial dependence; *Theobroma cacao* L.

ABSTRACT

Cacao is a species of great economic and social importance. Expanding the area grown with this crop has been limited by its climatic requirements. Agroclimatic zoning for agricultural sector and creation of land suitability maps by fuzzy logic contribute to such production expansion. In this sense, this study aimed to develop rainfall zoning for cacao in Bahia state using the fuzzy logic method. The used data came from rainfall historical series of 519 meteorological stations distributed throughout the state. Geostatistical analyses were used to quantify the spatial dependence degree of studied variable and kriging was used to develop maps representing mean monthly rainfall. These maps were submitted to continuous classification by fuzzy mapping for identification of high-risk areas for cocoa growing based on rainfall. Based on the fuzzy method, the southern mesoregion of Bahia state presented the highest rainfall uniformity, suggesting that this area is more suitable for cocoa growing.

INTRODUCTION

Brazil is the sixth largest cocoa beans producer worldwide, with a 5% share in world production and exporting its products mainly to the United States and Argentina (Franck et al., 2017). In Brazil, cocoa production is concentrated in Bahia state, which produces 141,110 tons and accounts for 62% of the national production, followed by Pará, Rondônia, Espírito Santo, Amazonas, and Mato Grosso (Estival & Corrêa, 2017).

Theobroma cacao L. is a species adapted to regions with mean monthly temperatures ranging from 18 to 32ºC and high rainfall (1150-2500 mm year^{-1}) well distributed throughout the year (Santos et al., 2018). Expansion of areas cultivated with this crop has been limited by the climatic conditions of each region. From 2015 to 2016, cocoa bean production decreased by around 42 thousand tons (IBGE, 2017), due to low rainfall. Within this context, studies on land suitability assessment may be performed through agroclimatic zoning.

Rainfall zoning techniques allows the assessment of effects caused by rainfall volume and intensity in a given region and provides the delimitation of areas with similar climate pattern (Sousa et al., 2013). In this sense, geostatistics may be a very useful tool, since it uses methods such as data interpolation by kriging and fuzzy logic to delimit these areas, facilitating agricultural planning and minimizing production loss risks. Thus, from a precision agriculture perspective, studies have shown that maps generated from a geostatistics standpoint have assisted rural producers in the use of localized technologies in response to spatial and temporal variabilities (Grego et al. 2014). However, geostatistics does not always add quality to the analysis, especially regarding climatic data that depend on data provision and information from weather stations. Another factor is the distance between weather stations, which is usually greater than the range indicated by the geostatistics technique.

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In addition, climatic phenomena such as rainfall are not static and demand the development of spatial analysis methodologies to generate, accurate information for land suitability zoning, which is confirmed by the intrinsic imprecision character of climatic unit classification (Cardoso et al., 2018). Fuzzy logic has been used in various agricultural and environmental sciences fields since it is a technique used when dealing with complex mathematical models that represent diffuse limits and have ambiguities, abstractions, and ambivalences, common in natural processes (Carvalho et al., 2016; et al., 2018).

It is necessary to look for spatial analysis methodologies, which may produce new information that represents more complex natural phenomena. Therefore, the research aimed to construct a rainfall zoning for cacao cultivation in Bahia state using the fuzzy logic.

MATERIAL AND METHODS

Bahia state is located to the south of Brazilian northeast region and has a land area of 564,732,642 km². This region has tropical humid (*Af*), rainy tropical (*Aw*), and hot arid (*BSh*) climates, according to the Köppen and Geiger classification system (Alvares et al., 2013).

The study was carried out based on data of historical series from the Brazilian Water Agency (ANA) for rainfall in Bahia state during 50 years (1961 to 2011). These data were expressed in water depth (mm) and were taken from 519 measurement points distributed throughout the state (Figure 1).

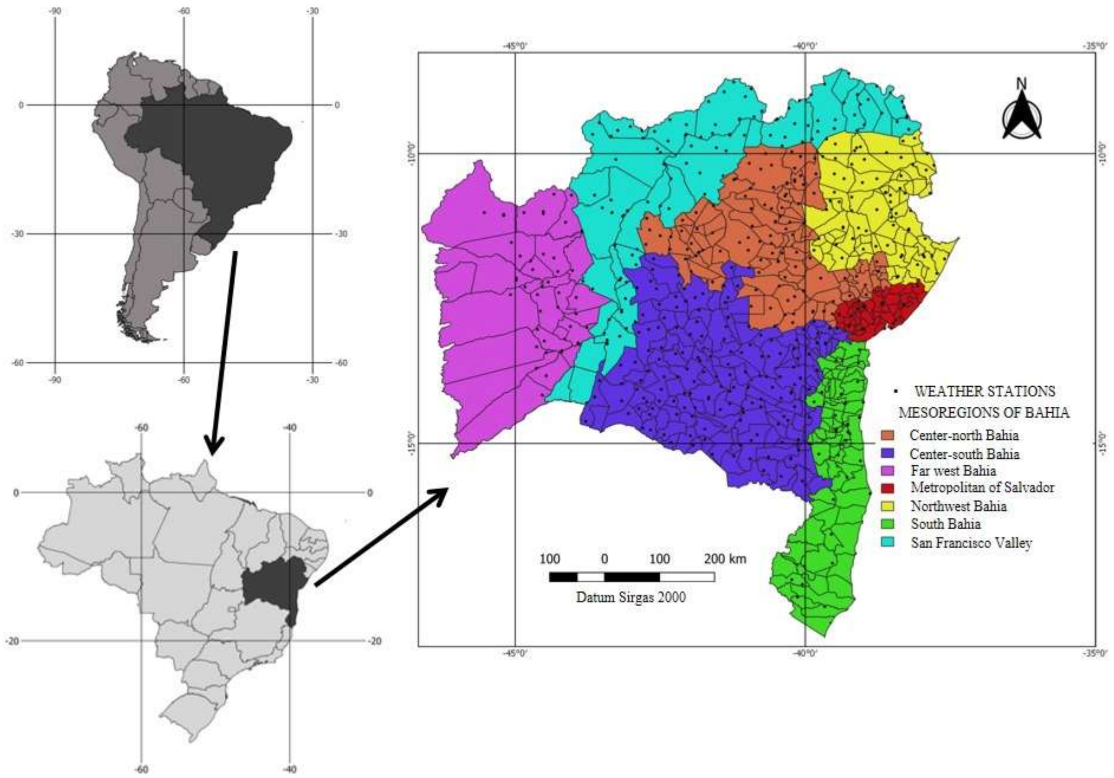


FIGURE 1. Map of mesoregions and meteorological stations in Bahia state.

Descriptive statistics of the dataset was used to determine the mean, median, maximum, minimum, standard deviation, asymmetry, kurtosis, and coefficient of variation (CV). The CV was classified according to Warrick & Nielsen (1980) into low (CV <12%), medium (12% <CV <24%), and high (CV> 24%). Data normality was tested by the Kolmogorov-Smirnov test at 1% probability level.

Data were submitted to geostatistical analysis to quantify the spatial dependence index (SDI) of rainfall in Bahia state by adjusting theoretical functions to experimental semivariograms models, based on the assumption of intrinsic stationarity, according to [eq. (1)]:

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

Where:

$\gamma^*(h)$ is the semivariance of one vector;

$N(h)$ is the number of paired values $[Z(x_i), Z(x_i + h)]$ separated by a vector h,

xi is a spatial position of variable Z, which refers to mean monthly value.

Experimental semivariograms were fitted to linear, Gaussian, exponential, and spherical theoretical functions, according to Deutsch & Journel (1998). These models were selected based on least square method, selecting those with the greater coefficient of determination (R^2), smaller residual square sum (RSS), and greater jackknife correlation coefficient. The fitting of theoretical models to the experimental variograms was performed using the coefficients nugget effect (C_0), sill (C_0 + C), and range (a).

The SDI was analyzed using the relationship and intervals proposed by Cambardella et al. (1994), as shown in [eq. (2)]. This index classifies spatial dependence into weak (SDI ≥ 75%), moderate (25% ≤ SDI < 75%), and strong (SDI < 25%). After the spatial dependence was verified, ordinary kriging geostatistical interpolation method was used to estimate variables in non-sampled sites.

$$IDE=\frac{Co}{Co+C1} \quad (2)$$

Where:

C_0 = nugget effect

$C_0 + C1$ = sill

The means of monthly rainfall were submitted to continuous classification using fuzzy mapping. A linear function was used for rainfall data association, as described by Bönisch et al. (2004) and Silva et al. (2010), according to the dataset with increasing values, as in eqs (3), (4) and (5):

$$MF_A\,(Z) = 0 \qquad \text{se } z \leq LI \quad (3)$$

$$MFA\,(Z) = \frac{1/\alpha}{z\text{-}LI} \qquad \text{se } LI < z > LS \quad (4)$$

$$MF_A\,(Z) = 1 \qquad \text{se } z \geq LS \quad (5)$$

Where:

α = difference between superior (LS) and inferior (LI) limits of two fuzzy sets belonging to an A set,

MF_A = pertinence function for variable Z

Fuzzy transition zone was based on the distribution slope of rainfall dataset with an increasing pattern (Figure 2).

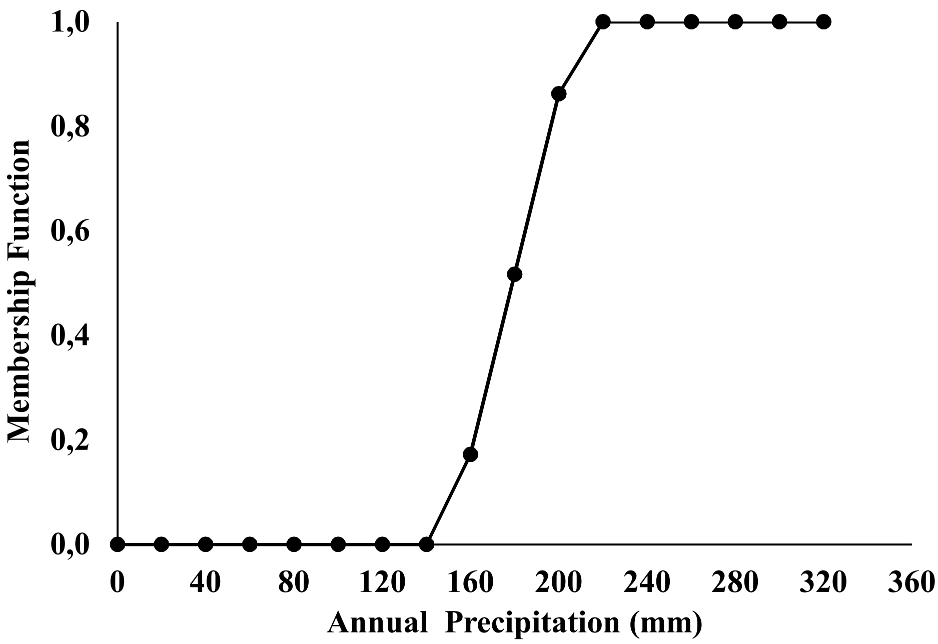


FIGURE 2. Fuzzy set for values of rainfall with an increasing pattern.

The class limits of the fuzzy set (Table 1) were defined according to optimal (ideal) intervals for cocoa development and production, as established by Santos et al. (2018). Thus, thematic maps for fuzzy classification were generated by the SURFER® software (Golden Software, Inc.).

TABLE 1. Defining criteria for fuzzy limits of rainfall classes.

Parameter	Class		
	Low	Ideal	High
Precipitation	< 96mm	96 a 208mm	>208mm

RESULTS AND DISCUSSION

The descriptive statistical analysis of mean monthly rainfall in Bahia state from 1961 to 2011 describes the sample data (Table 2) by means of measures of position (mean and median) and dispersion (minimum and maximum values, deviation standard, and CV), and coefficients of symmetry and kurtosis.

TABLE 2. Descriptive statistics of monthly rainfall data (mm) from the historical series between 1961 and 2011, in Bahia state, Brazil.

Month	Mean	Median	Minim	Maxim	DS[1]	CV[2]	S[3]	K[4]	KS[5]
Jan	161.58	151.77	110.18	327.33	42.42	26.25	1.16	1.37	0.113**
Feb	168.94	164.49	110.18	309.62	43.43	25.71	0.67	-0.01	0.088**
Mar	166.49	160.06	110.18	292.66	42.39	25.46	0.63	-0.31	0.092**
Apr	140.35	131.41	110.18	268.44	29.01	20.67	1.49	2.47	0.149**
May	125.91	117.79	110.18	292.46	21.37	16.97	2.67	11.38	0.231**
Jun	134.26	123.71	110.18	253.37	27.58	20.55	1.59	2.29	0.193**
Jul	153.06	140.66	110.18	532.91	45.53	29.74	2.38	11.24	0.173**
Aug	135.32	126.07	110.18	276.26	26.63	19.68	1.57	2.92	0.173**
Sep	132.27	117.79	110.18	246.12	28.75	21.73	1.47	1.32	0.227**
Oct	163.28	140.74	110.18	318.38	58.76	35.98	1.18	0.19	0.200**
Nov	150.94	137.44	110.18	365.02	43.83	29.04	1.68	2.82	0.190**
Dez	148.79	137.44	110.18	713.27	43.07	28.94	5.36	60.71	0.185**

[1]DS: deviation standard; [2]CV: coefficient of variation; [3]S: symmetry; [4]K: kurtosis; [5]KS: Kolmogorov–Smirnov test; ** significant at 1% of probability.

Considering the set of increasing values, data descriptive analysis (Figure 2) highlights an asymmetric distribution to the right of the curve slope, in accordance to the central trend values (mean and median), which were distant from each other (Table 2). However, central trend measures were the nearest in February and March (Table 2), indicating data distribution symmetry, confirmed by asymmetry coefficient and kurtosis near zero. According to Cardoso et al. (2018), mean and median patterns are confirmed by the asymmetry and kurtosis tests, because, as mean values decrease compared to median ones, the more the asymmetry and kurtosis values will approach zero, presenting less variability, as evidenced in this study. Normal distribution was observed in all the months, according to the Kolmogorov-Smirnov test at 1% probability. This occurs because although rainfall does not follow a regular pattern, monthly means does. According to Cressie (1991), data normality is not a geostatistics requirement, but elongated tails in the shape of distribution are undesirable, as observed in the results.

According to the CV (%) classification proposed by Warrick & Nielsen (1980), data variation in this study was medium to high in all months, with CV values between 16.97 and 35.98%. This result was expected since rainfall indexes (minimum and maximum) in Bahia state have a large variation, depending on the month.

Geostatistical analysis of rainfall in Bahia state (Table 3) showed spatial dependence for all months, which is justified by semivariograms with well-defined sill (C_0 + C). Therefore, the hypothesis of spatial dependence is met since minimal spatial dependence is required for geostatistical analysis (Lima et al., 2013). A range is an important parameter of a semivariogram model, allowing practical interpretations by indicating a semivariance pattern as a function of the distance between two points with spatial dependence (Almeida et al., 2017). Therefore, interpolations occurred at closer spacings than those sampled, for higher accuracy in estimation, and hence, data were fitted to the semivariogram model.

TABLE 3. Parameters of experimental semivariograms adjusted for the mean monthly rainfall between 1961 and 2011 in Bahia state, Brazil.

Month	Model	[1]C_0	[2]C_0+C	[3]R	[4]R^2	[5]$C_0/(C_0+C)$	[6]SDI	Jack-Knifing	
								Mean	[7]DS
Jan	Exp	0.363	1.882	459.90	0.956	19.28	Ft	-0.006	0.900
Feb	Exp	0.317	1.891	436.20	0.964	16.76	Ft	-0.003	0.905
Mar	Exp	0.501	1.853	384.00	0.917	27.04	Md	0.000	0.802
Apr	Exp	0.202	0.880	366.00	0.947	22.95	Ft	-0.009	0.897
May	Exp	0.265	0.530	349.80	0.871	50.00	Md	-0.012	0.855
Jun	Exp	0.093	0.800	234.00	0.806	11.63	Ft	-0.018	1.026
Jul	Exp	0.576	2.100	306.90	0.901	27.43	Md	-0.007	0.930
Aug	Exp	0.126	0.767	186.00	0.904	16.43	Ft	0.013	0.902
Sep	Exp	0.148	0.871	471.30	0.941	16.99	Ft	-0.023	1.040
Oct	Exp	0.337	3.471	614.10	0.988	9.70	Ft	-0.007	0.979
Nov	Exp	0.291	2.034	648.30	0.975	14.31	Ft	-0.008	1.018
Dez	Exp	0.809	2.330	974.10	0.856	34.72	Ft	-0.013	1.011

[1]C_0: nugget effect; [2]C_0+C: sill; [3]R: range; [4]R^2: model determination coefficient; [5]$C_0/(C_0+C)$: nugget effect and sill relation to classificate the SDI; [6]SDI: spatial dependence index; [7]DS: deviation standard of semivarigram model; Exp: exponential.

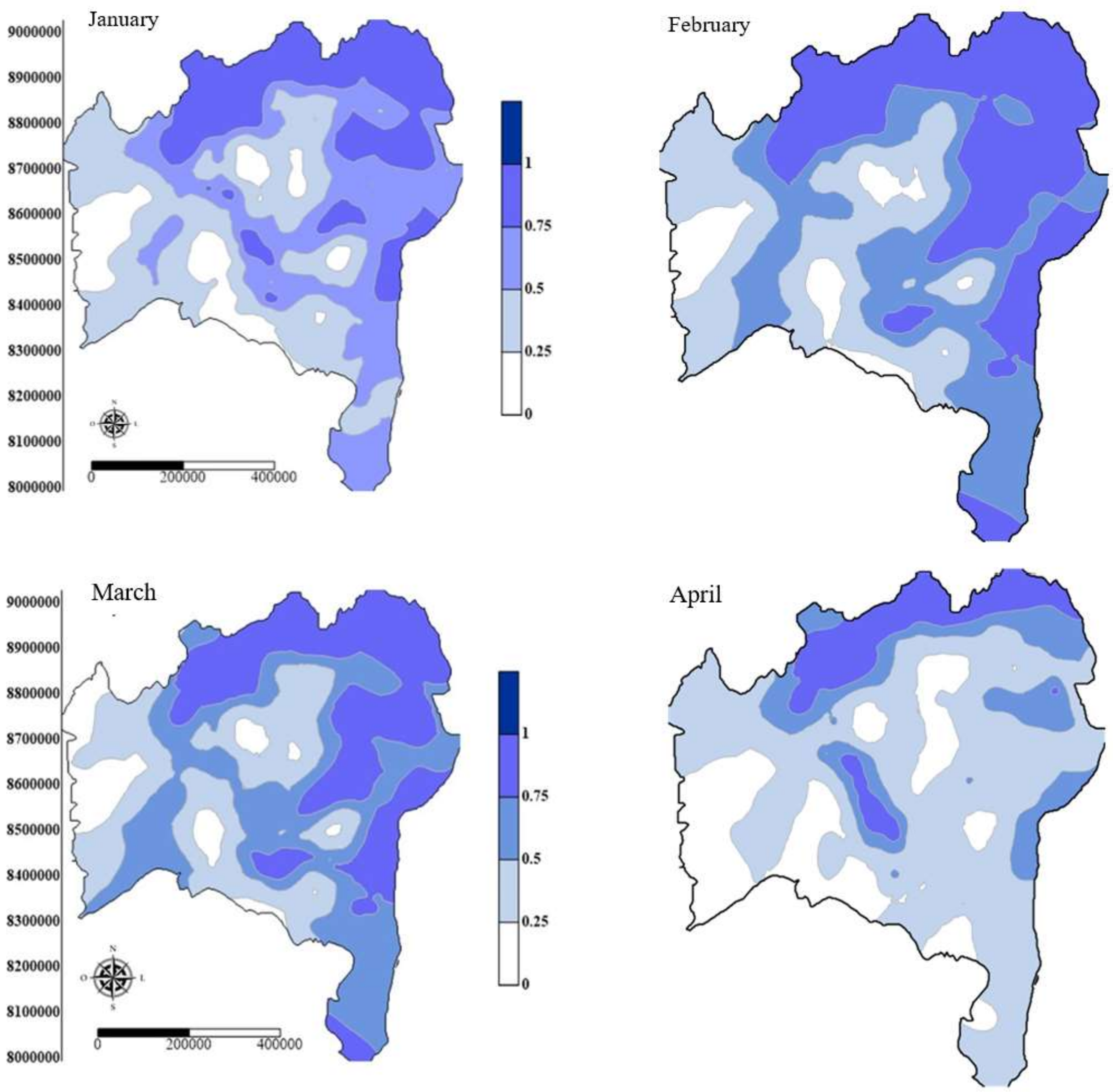
The exponential model was the best fit for the experimental semivariogram for rainfall. In similar studies by Mello et al. (2012) in Espírito Santo state and by Cardoso et al. (2018) also in Bahia state, the exponential model was also the best fit for the semivariogram for this climatic element. These results may interfere with both cross-validations of interpolation and final map quality, for considering different values of range (a). This is because the cross-validation correlation coefficient is one of the selection criteria for the semivariogram model; the higher the value, the better the fit.

According to the classification described by Cambardella (1994), the SDI for the historical series of mean monthly rainfall was considered strong (Table 3) except for March, May, and July, when it was moderate. For Franco & Silva (2016), the existence of spatial dependence is fundamental in geostatistics for the drawing of high-reliability kriging maps.

The semivariogram range (a) for rainfall (Table 3) varied from 186 km (August) to 974.10 km (December). Spatial variability was assessed using spatial dependence range (a) values, indicating that, for most months, monthly rainfall has high spatial variation. This is due to a major discrepancy between different regions within the state, from places (near the coast) where rains are evenly distributed over the year to those where they are uneven (semiarid region). In general, the highest values of range (a) were observed during spring-summer months while the lowest in autumn-winter ones, showing the seasonal influence on the rainfall spatial pattern in Bahia state.

The spatial variability was high in the entire state except for the north region of São Francisco valley, according to the fuzzy thematic maps (Figure 3) for classification of mean monthly rainfall. Such variability is due to an increase in the values of the range (a), in other words, the larger the range, the smaller the spatial discontinuity.

Overall, the southern mesoregion of Bahia state has greater rainfall uniformity throughout the year except in May, September, and October (Figure 3), as these months had pertinence close to zero, indicating unfavorable rainfall conditions for cocoa growing, which has an ideal average water demand between 96 and 208 mm^{-1}, according to Santos et al. (2018).



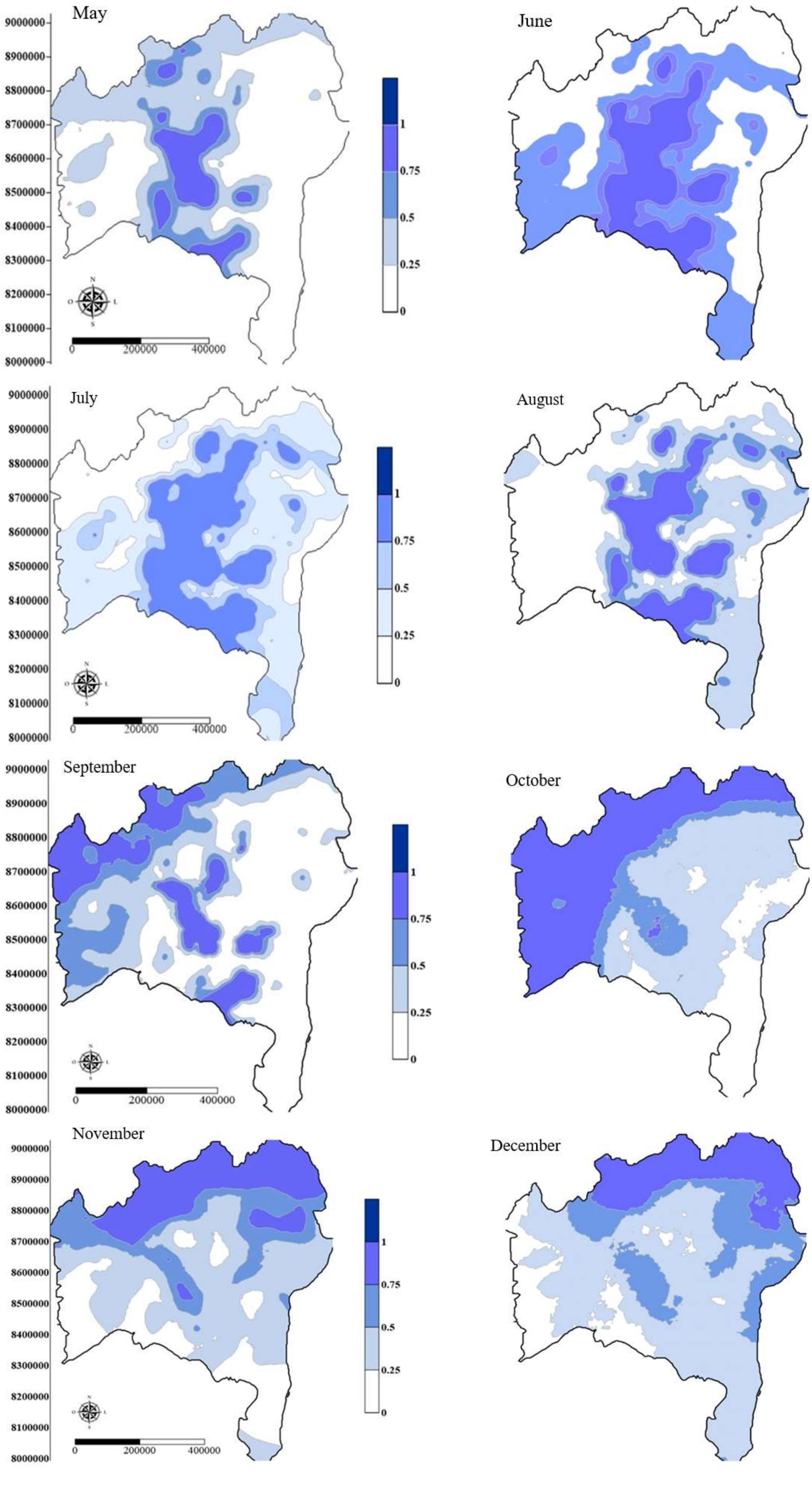


FIGURE 3. Fuzzy thematic maps for classification of mean monthly rainfall between 1961 and 2011 in Bahia state, Brazil.

The maps in Figure 3 show areas potentially suitable for growing cacao within Bahia state, based on the historical monthly rainfall data. The southern mesoregion presents the lowest rainfall risks for cocoa growing throughout the year, while the other mesoregions have higher risks. This fact is due to the greater spatial variability and, although these areas fall within the pertinence range (0-1), which means that cacao could be grown therein if rainfall index is considered, that is, potential areas of expansion for cocoa growing. Dourado et al. (2013) identified five different rainfall zones within Bahia state, of which the south had a higher rainfall volume and relatively regular rains throughout the year, confirming our findings. According to those authors, under regular conditions, the south mesoregion has the lowest risk of weather anomalies.

By using data interpolation by fuzzy logic, Ferreira (2012) defined management units and observed that such technique enables the description and modeling of climatic variables, allowing defining a decision surface and easing climatic categories.

Rainfall spatial variability has been shown in several scientific studies, supporting the results obtained in our research. For Cardoso et al. (2018), rainfall spatial-temporal distribution has a direct impact on the natural sustainability of different ecosystems. Marcuzzo et al. (2012) used monthly and annual averages of a 30-year period to map rainfall volume and seasonality in Mato Grosso state, identifying periods of major and minor rainfall and climatic anomalies. These authors stated that rainfall spatial distribution studies provide an indication of areas prone to agriculture, allowing the adoption of precision agriculture and using techniques to reduce productivity loss.

The fuzzy logic method allowed identifying rainfall changes in different months along the year and can be used in precision agriculture since it showed a good performance to characterize and map uncertainties of the studied phenomenon in the state of Bahia, Brazil.

CONCLUSIONS

1) Fuzzy logic provided satisfactory results.

2) The southern mesoregion of Bahia state presented the highest uniformity for the studied variable and can be classified as the most suitable to grow cocoa crops.

3) Although the other mesoregions had a higher spatial variability, they were classified as potential areas for expansion of cocoa growing.

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