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SPACE TEMPORAL VARIABILITY NORMALIZED DIFFERENCE VEGETATION INDEXIN THE SEMIARID PERNAMBUCANO BASED ON IMAGE TM / LANDSAT 5

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Abstract

Rainfall is one of climate elements that influence the spatial and temporal variation of plant cover in any region and, in particular, in the caatinga semiarid Northeast. Before this, there was a need to examine relations of seasonal rainfall in the semiarid region of the State of Pernambuco with classes of use and soil cover and changes in vegetation Index (NDVI) for Normalized Difference, using principal component analysis and remote sensing techniques, being these determinations the main goals of this work. Four images of the Thematic Mapper (TM) sensor, the satellite Landsat 5, dated 12/12/1991, 12/9/1996, 12/13/2003 and 11/27/2009, formed the experimental unit, whose variables were estimated using the algorithm Surface Energy Balance Algorithms for Land (SEBAL), in addition to the daily rainfall data of 1996 and 2009 and the series 1975 to 2010. The main results indicated that the amount and distribution of rain influenced on the surface temperature and the values of the indexes of reflection and NDVI, excelling by high recovery power plant, as the coverage that occurred in the year 1996, and expressed by the greatest value of NDVI. It is concluded that remote sensing techniques associated with those of main components were efficient to quantify the spatio-temporal variability of climate and vegetation index of the normalized difference of semiarid conditions.

Keywords: Spectral vegetation indexes, rainfall, seasonal caatinga vegetation.

1 Introduction

Much of northeastern Brazil forms the semiarid Northeast, where the annual average temperature ranges from 24 to 28 º C and features an irregular spatial and temporal in the amount and distribution of rainfall and high evaporation rate (Strang, 1972). This region is often subject to the effects of droughts, being most pronounced in areas called "Drought Polygon", whose average annual rainfall is less than 500 mm, reaching extreme values below 400 mm in the semiarid part of Paraíba and Pernambuco, thus as near Petrolina in the São Francisco Valley (Strang, 1972).

The Lower Basin of the São Francisco is the main center producer and exporter of table grapes in Brazil, especially the municipalities of Santa Maria da Boa Vista and Petrolina, in Pernambuco State, with 54% of the cultivated area, followed by municipalities Juazeiro, Casa Nova, Curaçá and SentoSé, in Bahia state, where the vine is of great socioeconomic importance by the number of jobs created. The area planted to this crop has expanded significantly in recent years, this region (Silva &Correia, 2000).

The vegetation is predominated by various morphological patterns depending on the geographical location and climatic conditions. A portion focuses on the semiarid savanna shrub, dense or open, it loses foliage during the dry season and earns foliage soon after the return of the rains (IBGE, 2004).

Contemporary studies focusing on physical and environmental geotechnology and employment have relevance in the scope of the geosciences, because from them, you can understand the general conditions of the landscape, contributing to the development of prognostic and geoenvironmental interpretations (Lang et al., 2009).

Currently, with access to products from satellite sensors such as images and multitemporalinterferometric data, it is possible to produce several products, including, maps of slope, contour lines, shaded terrain models, highlighting the importance of architecture (structures, modeled , drainage network, drainage hierarchy, among others) in various scales (local, regional and continental) providing various types of analyzes within the geoenvironmental studies (Valeriano, 2008; Florenzano, 2008).

Houborg et al. (2007) developed a numerical method combining vegetation indices and biophysical parameters using Terra MODIS-Aqua in a region of Denmark. The results indicated a relationship between LAI measured and estimated 62%, 46% and 63% of the variance in the areas of cultivation of barley, wheat and on forest sites, respectively. Dantas (2008) used data from the sensor system AVHRR / NOAA and Landsat 5 / TM to find a functional relationship between albedo, LAI, NDVI, SAVI and vegetation fraction on different targets near Quixeré - EC.

Gurgel (2003) analyzed the connections between NDVI and variability of climatological annual and interannual in Brazil, using the technique of principal component analysis (PCA) to monthly data derived from AVHRR NDVI for the period from January 1982 to December 1993, the results of which show that the PCA applied to characterize NDVI provides annual and interannual variability of these types of vegetation related to climate variability.

According to Anderson (1984), there are basically two ways to classify multivariate analyzes: those that allow you to extract information about the independence between the variables that characterize each element, such as factor analysis, clustering, canonical, spatial and multidimensional main components, and which allow to extract information about the dependency between one or more variables or in relation to one another, such as multivariate regression, multiple contingency of variance and multivariate discriminant.

Weare&Nasstrom (1982) highlighted that the most important points of using the method of Principal Component Analysis are: (i) the satisfactory description of changes in a complex field from a relatively small number of functions, involving the temporal coefficients; (ii) the fact that the empirical functions derived from this technique are favorable for physical interpretations, (iii) the PCA is suitable for spatial fields on regular grids or not. This statistical method has become more popular in atmospheric sciences from the work of Lorenz (1956), who called the technique of empirical orthogonal functions (Empirical Orthogonal Function - EOF). According to Wilks (1995), both names are used and refer to the same set of procedures.

The PCA has a broad applicability, for example, can be used to extract dynamic independent standards and physical to represent natural variability or fluctuations. Kim and Wu (1999) highlighted an essential application of PCA in climate studies in the areas of forecasting, estimation and detection of climate change.

In the present study we used the PCA to reduce the size of the data set of precipitation and the NDVI seeking to maintain most of the variability in the original sets. These analysis techniques allowed us to evaluate the influence of rainfall variability in spatial and temporal variability of vegetation in semiarid Pernambuco.

2 Material and methods

The study area shares parts of the territory of the municipalities of Petrolina-PE, Lagoa Grande-PE and Juazeiro-BA. The clipping has 1700.0 km^2 resulting in a rectangle with the following coordinates: upper-left corner of -8.73° and -40.41°, and the lower right corner of -9.08° and -40.01° (Figure 1) . The climate of the region is semiarid, with mean annual temperature of 27º C, rated by BSwh (Köppen-Geiger, 1928). Due to the characteristics of climate and temperature associated with the intertropical geographical location, potential evaporation is very high, being of the order of 3,000 mm annually.

Also, are high insolation and low relative humidity of the air. The dry season is predominant, approximately 6 to 8 months. The average annual rainfall is of the order of 400 to 650 mm, which occurs irregularly and concentrated to 2 to 3 months of the year, occurring heavy rainfall (120 to 130 mm) in a 24 hour period. The savanna vegetation, predominant in almost any area ofthe Lower Basin of the São Francisco Valley, consists of formations xerophilous, woody, deciduous, usually spiny, with presence of succulent plants, both with standard tree like shrub, dense and sparse with seasonal herbaceous (Andrade Lima, 1992).

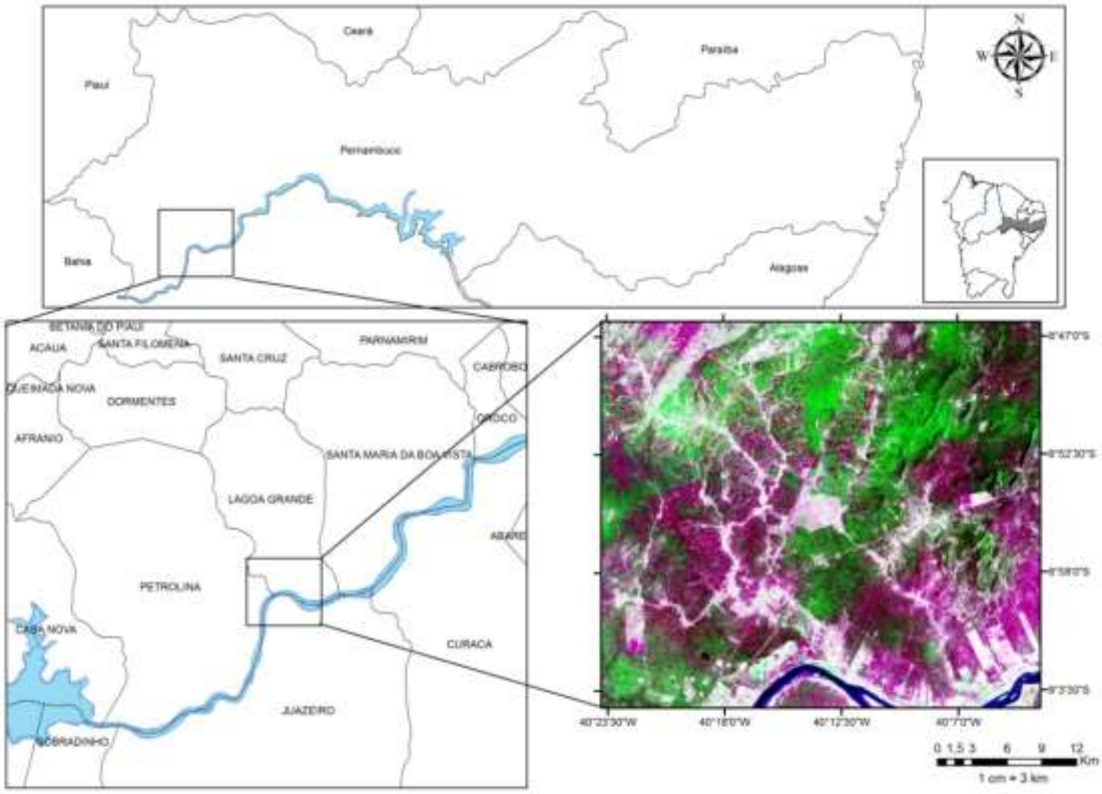

Figure 1.Location of the study area.

2.1 Meteorological variables

We used daily data of rainfall from meteorological stations Cabrobó (-8.50°, -39.31°), Ouricuri (-7.90°, -40.03°) and Bodocó (-8.27º, -40.6º) for the months of November and December of 1996 and 2003, such stations make up the network of meteorological monitoring of the National Institute of Meteorology (INMET). The basis of monthly data for the period 1975 to 2010 used in this study comes from the weather station of Bebedouro (-9.15°, -40.36°), which is inserted in the research unit of EMBRAPA-semiarid (CPATSA).

2.2 Remote sensing data

The TM - Landsat 5 selected for this study were obtained through the website of the National Institute for Space Research (INPE), referring to the orbit 217 and the point 66 of the day: 12 December 1991 09 December 1996 December 13, 2003 and November 27, 2009 (Figure 2).

For the image processing used the software ERDAS Imagine 9.2, employing tasks of re-sampling, stacking, clippings and georeferencing of images and mathematical operations in the calculation of surface parameters. Table 1 contains the date, day of the year of order (DYO) and time of the satellite passage (GMT - Greenwich Mean Time), and the correction of the eccentricity of Earth's orbit (dr) and cosine of solar zenith angle (cos Z) representing the time the satellite passed over the study area

Table 1. Date, day of year order (DYO), Greenwich Mean Time (GMT), elevation angle of the sun (E) and solar zenith angle (Z).

Date	DYO	Timetable		Angles	
		(GMT)	Local	E (°)	Z (°)
12/12/1991	346	12:12:28	09:12:28	53.55	36.45
09/12/1996	343	12:09:19	09:09:19	53.39	36.61
13/12/2003	347	12:26:31	09:26:31	56.55	33.45
27/11/2009	331	12:38:27	09:38:27	61.22	28.78

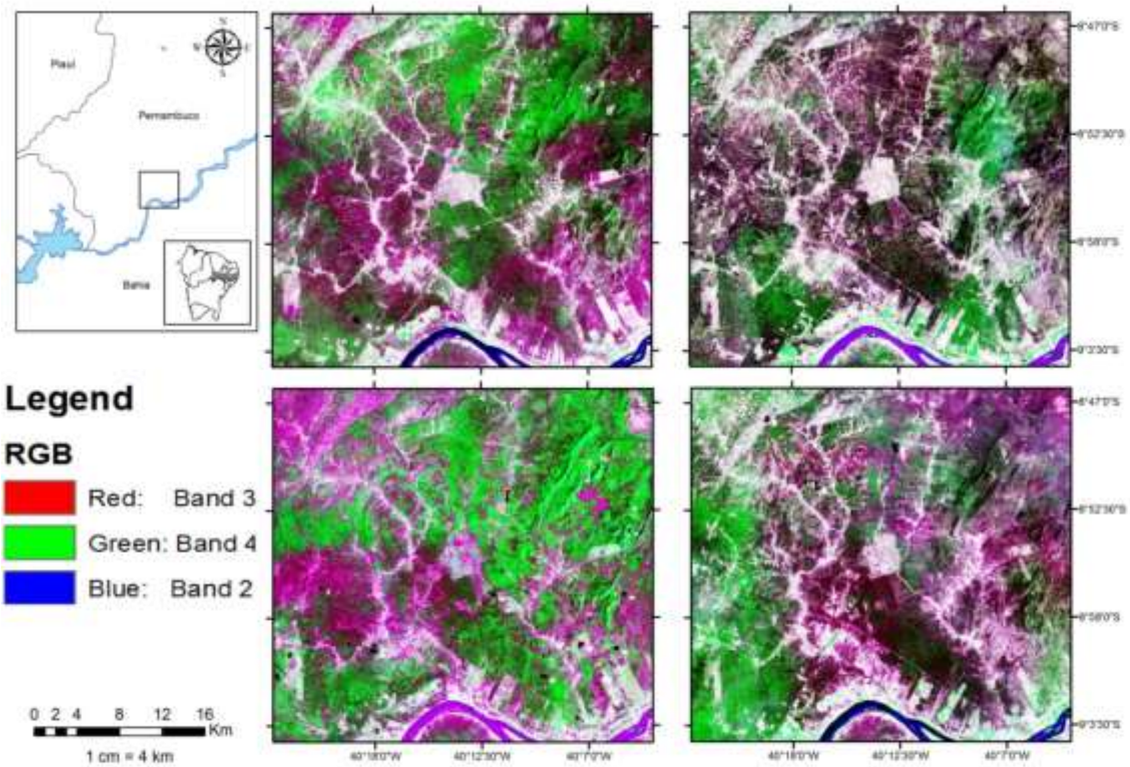

Figure 2. Compositionof RGB342 of TM - Landsat 5 for: December, 12/1991 (A), December, 09/1996 (B), December, 13/2003 (C) e November, 27/2009 (D).

2.3 Radiometric calibration

After making the cut image, proceeded to radiometric calibration of the seven spectral bands of the TM, which is to convert the digital number (DN) of each pixel in spectral radiance and banda (Lλi in W m-2 sr-1 mM-1) being determined by Equation (1), proposed by Chander& Markham (2003):

$$L_{\lambda i} = a_i + \frac{b_i - a_i}{255} ND \quad \textbf{(1)}$$

where: $L\lambda_i$ is the spectral radiance of each band, a and b are the minimum and maximum radiances obtained by calibration of TM - Landsat 5, whose values are shown in Table 2, ND is the digital number (integer between 0-255) i corresponds bands (1, 2, 3, ..., 7) TM - Landsat 5.

2.4 Monochrome reflectance

The reflectance mono (ρλi) in top the atmosphere to bands 1 to 5 and 7, given by the ratio between the flow of solar radiation and the reflected incident solar radiation was determined by Equation 2 proposed by (Chander & Markham, 2003):

$$\rho_{\lambda i} = \frac{\pi . L_{\lambda i}}{K_{\lambda i} . \cos Z . dr} \quad \textbf{(2)}$$

where: Kλi is monochromatic solar irradiance in each band (W m^{-2} μm^{-1}), whose values are shown in Table 4, $Z$is solar zenith angle (degrees); dr is the inverse of the square of the relative distance Earth-Sun obtained by Equation (3):

$$dr = 1 + 0.033 \cos\left(\frac{DOA2\pi}{365}\right) \qquad \textbf{(3)}$$

where: DOA is the day of year order.

Table 2. Calibration constants and spectral solar irradiance at the top of the atmosphere for TM - Landsat 5.

Band	a (Wm^{-2}sr^{-1}μm^{-1})	b (Wm^{-2}sr^{-1}μm^{-1})	$K_{\lambda i}$(Wm^{-2}mm^{-1})
1	-1.52	193.0	1957
2	-2.84	365.0	1826
3	-1.17	264.0	1554
4	-1.51	221.0	1036
5	-0.37	30.20	215.0
6	1.24	15.30	-
7	-0.15	16.50	80.67

2.5 Vegetation Index

The Index Normalized Difference Vegetation (NDVI) is an indicator of the quantity and condition of the vegetation of the earth surface and the values range from -1 to +1. The NDVI is obtained by dividing the difference of the reflectivities near infrared (ρ4) and red (ρ3) and the sum obtained between them. according to the description of Equation (4) cited by Allen et al. (2002):

$$NDVI = \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3} \qquad \textbf{(4)}$$

2.6 Statistical Analysis

The analysis of the temporal variability of monthly precipitation for the weather station Bebedouro-PE. between 1975 - 2010 was performed by Principal Component Analysis. The data analyzed in this study were organized according to the PCA from an nxp matrix data. where each line (n) represents the year used in the study (p) the months of each year.

The technique consisted of transforming a set of original data into a new set. that is. scores. wherein the components preserve variability and are not correlated with each other. thus facilitating the spatial separation of temporal fluctuations.

The technique is based on the procedures reported by (Storch & Zwiers. 2000) which consist in relation to a symmetric quadratic matrix can be decomposed into other matrices that preserve variability.

For this study we used the correlation matrix. whose degree of association between two random variables X and Y is expressed by Equation (5):

$$Cor_{(X,Y)} = \frac{Cov_{(X,Y)}}{\sqrt{Var_{(X)}\ Var_{(Y)}}} \qquad \textbf{(5)}$$

where. Cov (X. Y) is the covariance of X and Y variables (Equation 6) and Var (X) (Equation 7) and Var (Y) (Equation 8) are the variances:

$$Cov_{(X,Y)} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Y_i - \overline{Y})}{n-1} \qquad \textbf{(6)}$$

$$Var_{(X)} = \frac{\sum_{i=1}^{n}(X_i - \overline{X})^2}{n-1} \quad \textbf{(7)}$$

$$Var_{(Y)} = \frac{\sum_{i=1}^{n}(Y_i - \overline{Y})^2}{n-1} \quad \textbf{(8)}$$

The matrices resulting from the decomposition of the correlation matrix provide the eigenvalues and eigenvectors are obtained by Equation (9):

$$\mathbf{M} = \underline{\mathbf{V}}\ \Lambda \underline{\mathbf{V}}^{T} \quad \textbf{(9)}$$

where: M is a correlation matrix of the original data pxp; V the matrix with the eigenvectors p x p;Λ the diagonal matrix with the eigenvalues p x p;V^T the transposed matrix with the eigenvectors p x p.

The normalized eigenvectors (weights of individual variation in each position) associated with each eigenvalue (collective weight of all positions) is defined by Principal Oscillation Pattern. whose function is to identify areas of greatest importance in partial explanation of each eigenvalue.

The combination of eigenvectors derived from the V matrix M and the original data produce new standardized Y variable set of principal component scores which are obtained by Equation (10):

$$\underline{\mathbf{Z}} = \underline{\mathbf{V}}^{T}\ \underline{\mathbf{Y}} \quad \textbf{(10)}$$

Finally scores represent the combination of spatial dispersion of the original data each time. and not correlated. Thus. it was possible to correlate all variable scores of rainfall in order to verify the relationships clearer. Every nonzero eigenvalue corresponds to a component with explanatory power of information expressed in percentage of the total variance.

3. Results and Discussion

From Table 3 it can be seen that the numerical values of the indices of normalized difference vegetation. for the days analyzed. ranged between -1.00 and -0.329 (minimum). maximum 0.775 to 0.963) and 0.260 to 0.592 (average). The highest daily amplitude occurred on December. 09/1996 with 1.963. and the lowest was 1.104 for the day December. 12/1991. Notes also mean that any one of the dates of the median differs and therefore fashion and therefore the distribution is asymmetrical. It is noteworthy also that the daily average dispersion (D P) is equivalent to more than 23% of average. with a maximum of 45.0% for the NDVI of the day december. 13/2003.

Negative values of NDVI generated from this study. as expected. characteristic values for the water bodies. In areas of native vegetation (Caatinga) values were above 0.35. As for the areas that suffer human actions. it was observed that the NDVI ranged between 0.1 and 0.35. This result are in the range found for the Semiarid Northeast. by Rodrigues et al. (2009). with NDVI values between 0.20 to 0.39 and 0.03 to 0.20. in the years 2000 and 2001. respectively. Also according to these authors. these values are characteristic of areas with sparse vegetation or no vegetation. typical of semiarid.

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Table 3. Minimum. maximum. mean. median. modeandstandard deviation (SD) rates ofnormalized difference vegetationinsemiarid .

Date	Minimum	Maximum	Mean	Median	Mode	SD
Dec.12/1991	-0.329	0.775	0.388	0.395	0.408	0.090
Dec.09/1996	-1.0	0.963	0.592	0.626	0.707	0.168
Dec.13/2003	-1.0	0.836	0.260	0.252	0.260	0.117
Nov.27/2009	-0.690	0.828	0.364	0.359	0.359	0.100

Silva et al. (2005). as well as for bare soil in the interior of Bahia and Pernambuco. whose NDVI values found for the same two years were 0.16 and 0.17. respectively. It is believed that the existence of these areas exposed soils shows anthropogenic where NDVI may vary from 0.05 to 0.30. as found by Huete& Tucker (1991).

In Figure 3 there are classes of NDVI for the study area. It is observed that on Sep.12.1996 (Figure 3B) that was showed the highest rate of normalized difference vegetation (greater than 0.42). It is believed that the higher values of NDVI in the study area. is a consequence of a rainy period occurred in November. However. according to the charts generated. it became evident the spatio-temporal vegetation thus showing that the forcing of the rainfall regime operates in substantially the characterization of space throughout the study period.

It is observed that the samples analyzed photographs of the days. there are big differences between NDVI deforested areas and areas with natural vegetation. In areas with evidence of anthropogenic alteration classes Index Normalized Difference Vegetation ranged from 0.037 to 0.35. characterizing thus soil with little or no vegetation. It is noteworthy. however. that vegetation is a reflection of the local climate. given that Paiva (2005) describes that in bare soil or sparse vegetation. surface temperature is highest and the lowest NDVI is. contrary to what may occur in soils fully covered by vegetation.

Through the application of Principal Component Analysis shows that the variability of NDVI is 71.1% is explained by the components 1 and 2. According to Table 4. the percentage of the total variance explained by the components 1. 2. 3 and 4. Each component represents a set of variables that characterize the variability of the data Index Normalized Difference Vegetation in the study area in the period 1991-2009.

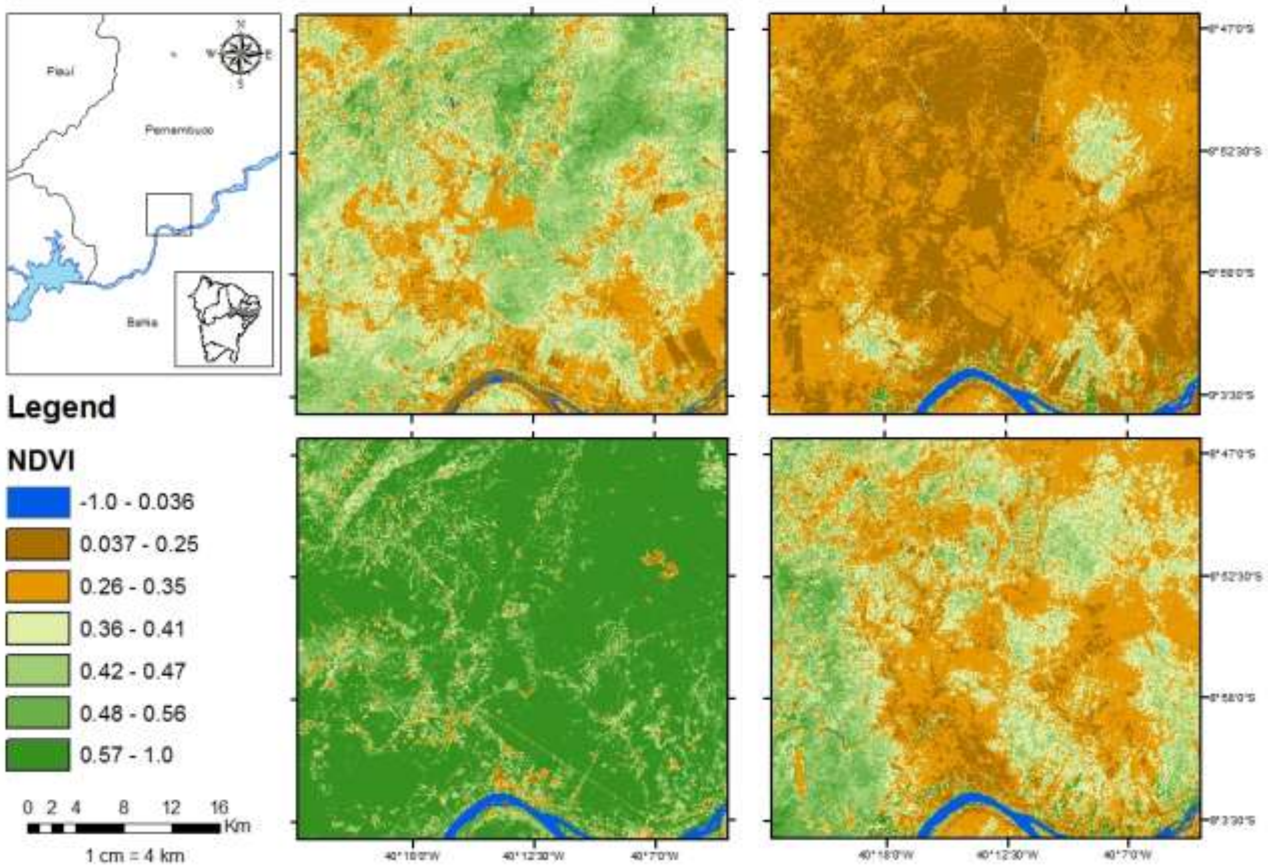

Figure 3.Index Normalized Difference Vegetation (NDVI) obtained by TM imaging sensor for day: dec.12.1991 (A), dec.09/1996 (B), dec.13/2003 (C) and nov.27/2009 (D) for the semiarid of the Pernambuco state.

The analysis of PCA (Table 4) shows that the variability in the data can be explained by the first two components. more meaningful. that have the largest eigenvalues or near 1. The eigenvalues obtained in the PCA who underwent rotation VARIMAX to detect which variables best represent the factors and thereby facilitate interpretation of results. The two first principal components (PCs) explain about 71.1% of the total variance of NDVI. namely 43.2%. the first component and 27.9% in the second component.

It is noteworthy also that the first rotated component explains 36.9% of the variance. and presented higher NDVI values associated with the days 12/12/1991 and 09/12/1996. Already. the second component explains 34.2% of the total variance and has higher values on dec.13/2003 and nov.27/2009 as shown in Table 5.

Table 4. Components. eigenvalues and percentage of total variance and accumulated in the initial conditions and rotated components of NDVI for the semiarid of the Pernambuco state.

Components	Initialconditions			Rotation components (VARIMAX rotation)		
	Eigenvalues	Variance		Eigenvalues	Variance	
		Total (%)	Acumulated (%)		Total (%)	Acumulated (%)
1	1.7	43.2	43.2	1.5	36.9	36.9
2	1.1	27.9	71.1	1.4	34.2	71.1
3	0.7	17.7	88.8			
4	0.4	11.2	100.0			

The spatial configuration of the first two factors are presented in Figures 4 and 5. respectively. The first factor (Figure 4) is well correlated with the images of Dec.12/1991 and Dec.09/1996. Areas with positive scores (values greater than 0.5) constitute the relevance of the contribution of the northeast and southwest of the study area.

The spatial distribution of the second factor (Figure 5) is well correlated between the dates of Dec.13/2003 and Nov.27/2009. Areas with positive scores (values greater than 1.0) constitute the relevance of the contribution of the south and northwest.

Table 5. Contribution of the two components. temporal variation.

Date	**Correlation**	
	Component 1	**Component 2**
Dec./12/1991	87.4%	-
Dec.09/1996	82.7%	-
Dec.13/2003	-	85.4%
Nov.27/2009	-	78.5%

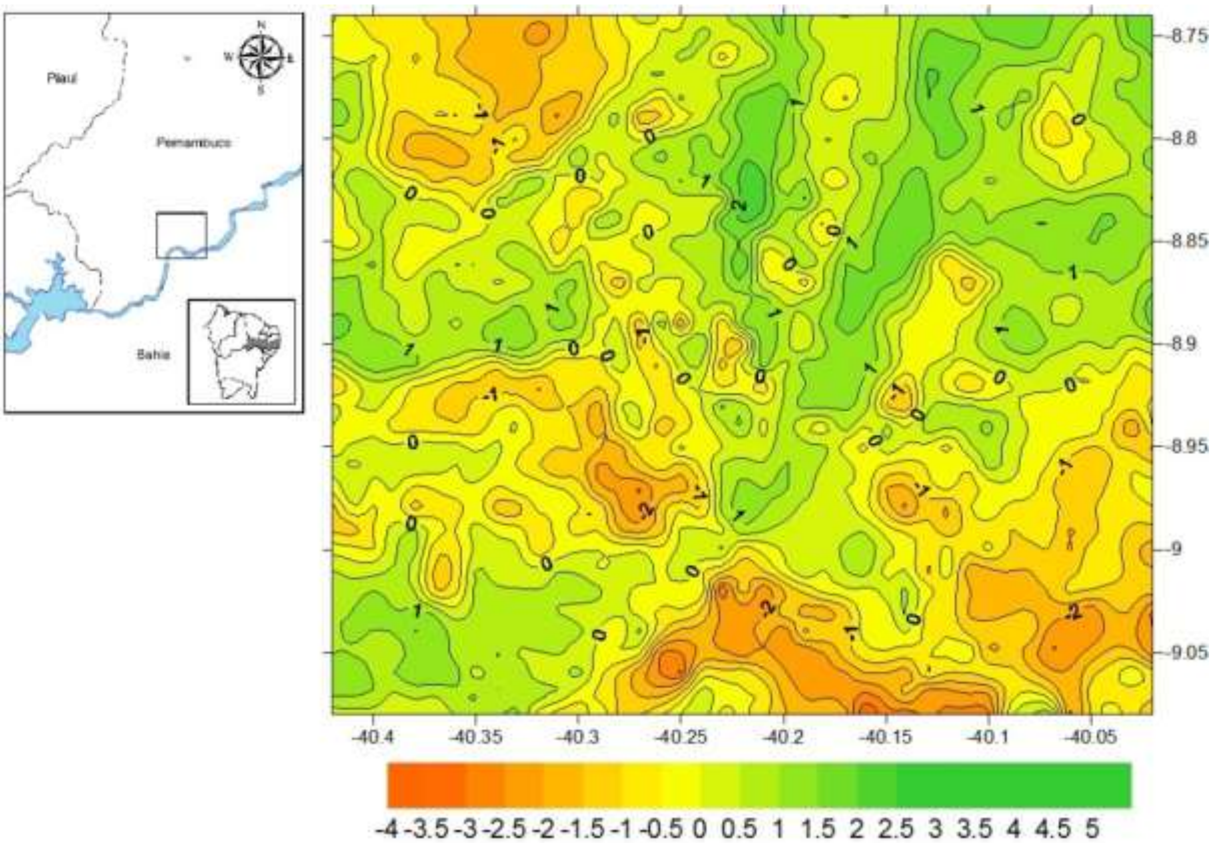

Figure 4. Spatial distribution of the first factor (score).

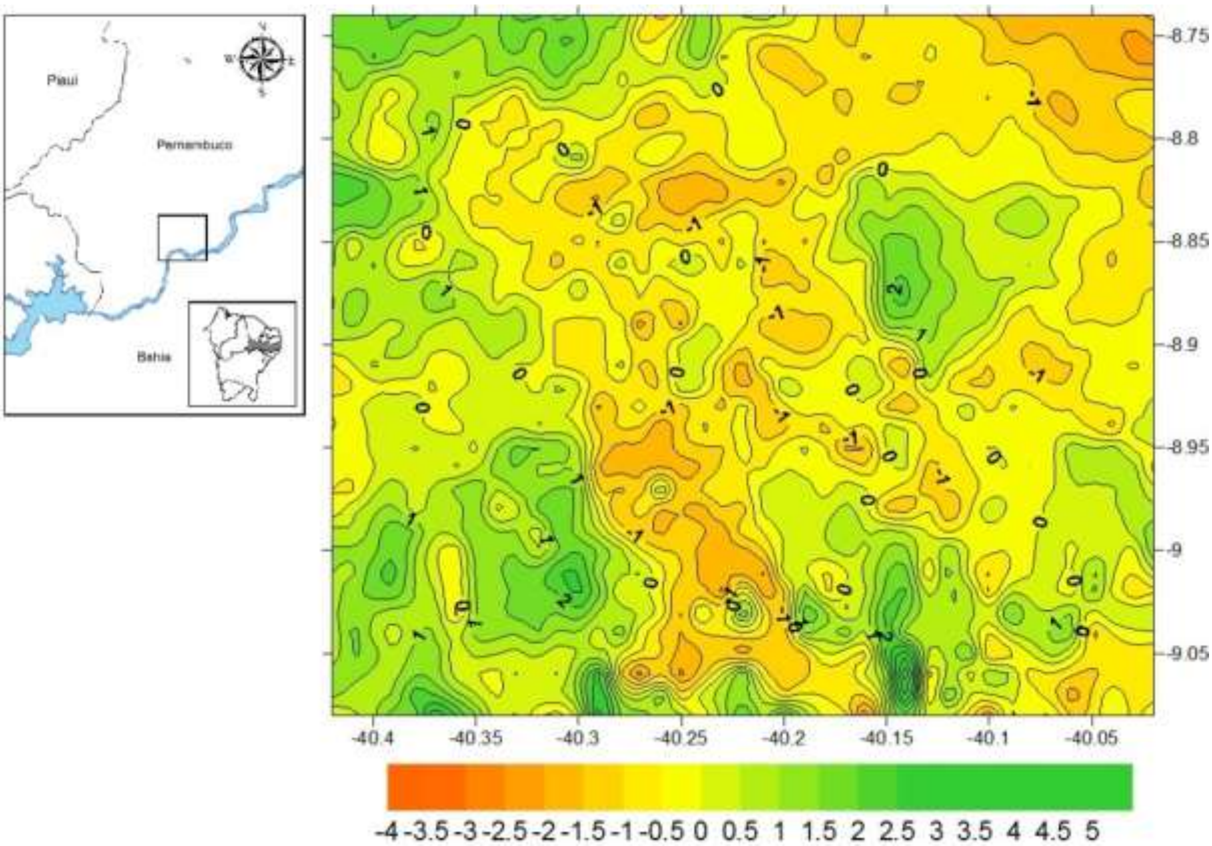

Figure 5. Spatial distribution of the second factor (score).

3.1 Patterns of spatio-temporal variability of surface parameters and precipitation

According to Figures 6 and 7 it is observed classification results of the images of NDVI for days Sep.12.1996 and Dec.13.2003 respectively associated with the data of rainfall. To facilitate interpretation of the results was performed supervised multispectral classification. which classified the region into vegetated areas. with urban or cultivation (Aur / Cult). exposed soil (SE) and water bodies (Ag). The vegetated areas were classified according to density of vegetation cover in four vegetation types (Vegetation Rala (VR); open vegetation (VA); Vegetation Transition (VT) and Dense Vegetation (RV)). following the methodology of Lawrence Landim (2004). where higher values of NDVI were associated with a higher density of vegetation and areas of exposed soil and water surfaces were associated with slice of NDVI values lower.

The areas with bare soil and sparse vegetation grew considerably when comparing the image of Sep.12.1996 (Figure 6A) with that of Dec.13/2003 (Figure 7A). Conversely. areas with open vegetation. dense transition and decreased during the study period. and the area with surface water. represented in the figure by the river São Francisco. hardly showed any change. The areas that showed greater variability in their coverage were those located on the banks of the São Francisco River and south of the region. possibly in the face of the expansion of irrigated crops in that area.

It is noteworthy. however. that forcing referring rainfall had direct influence on the result of the classification of the NDVI. in view of the increase in land cover in the study region after a rainy period. this feature is observed when comparing the quality of beginning of the rainy season in the study area (November-December).

Figure 6B shows the distribution of rainfall in the study area in the period from 01 November to 15 December 1996. In three locations (Cabrobó, Ouricuri and Bodocó) was minimal records of rainfall 15 days before (November 17). when the satellite pass. and recorded more than 80 mm on 03 December. In a study of the response of NDVI as a function of precipitation Goncalves (2008) reported that there is a direct relationship between precipitation and NDVI. ie when an increase in precipitation occurred also increased NDVI.

According Weng & Lu (2008). NDVI behavior is strongly influenced by rainfall. and the time lag between them. With respect to 2003. it is observed (Figure 7B). a relatively long period of drought before the satellite pass.

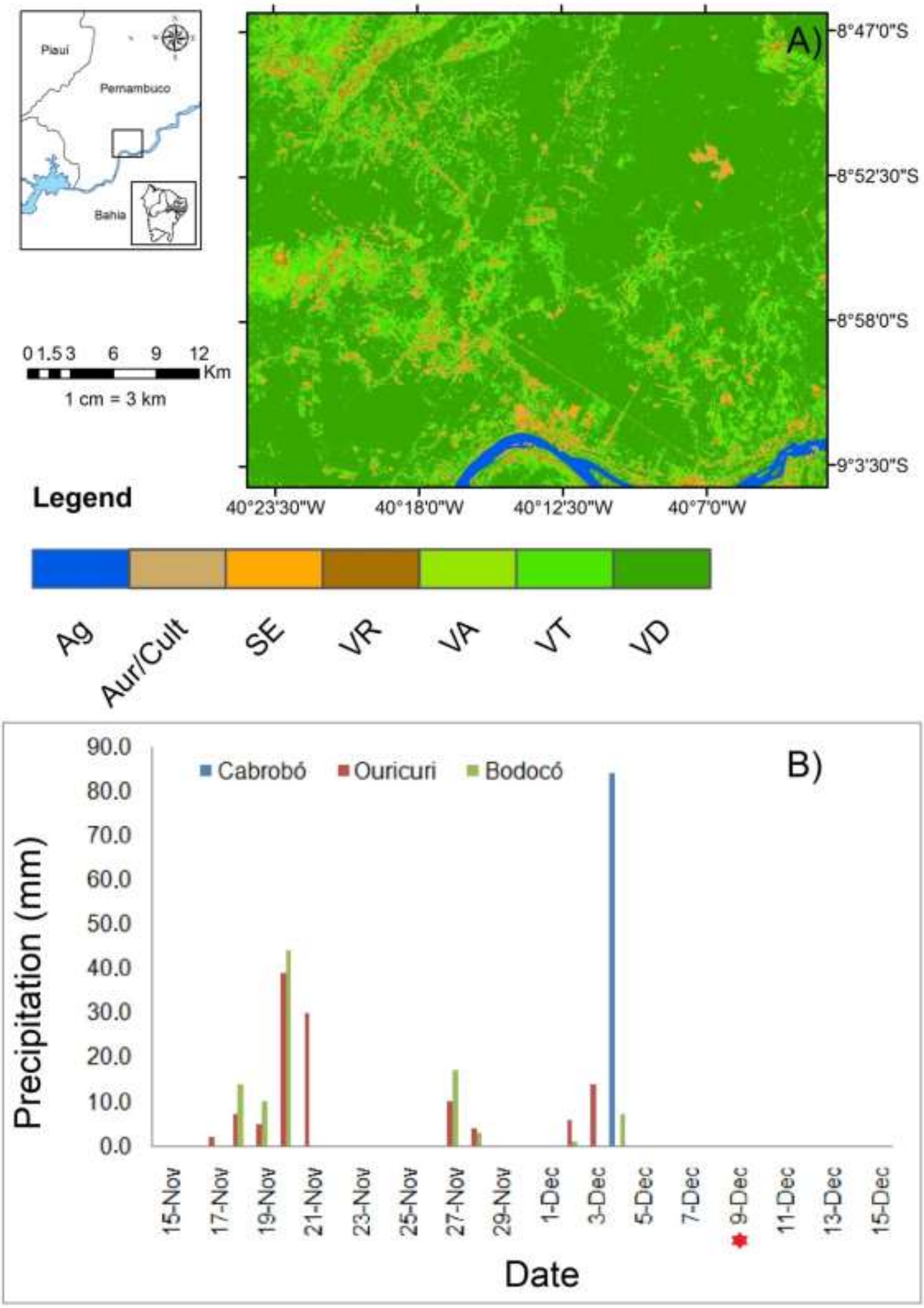

Figure 6. Thematic map of land cover for the study area. according to the NDVI for each pixel of the day Dec.09.1996 (A). associated with the distribution of rainfall during the period from November 15 to December 15. 1996 (B) for semiarid of the Pernambuco state.

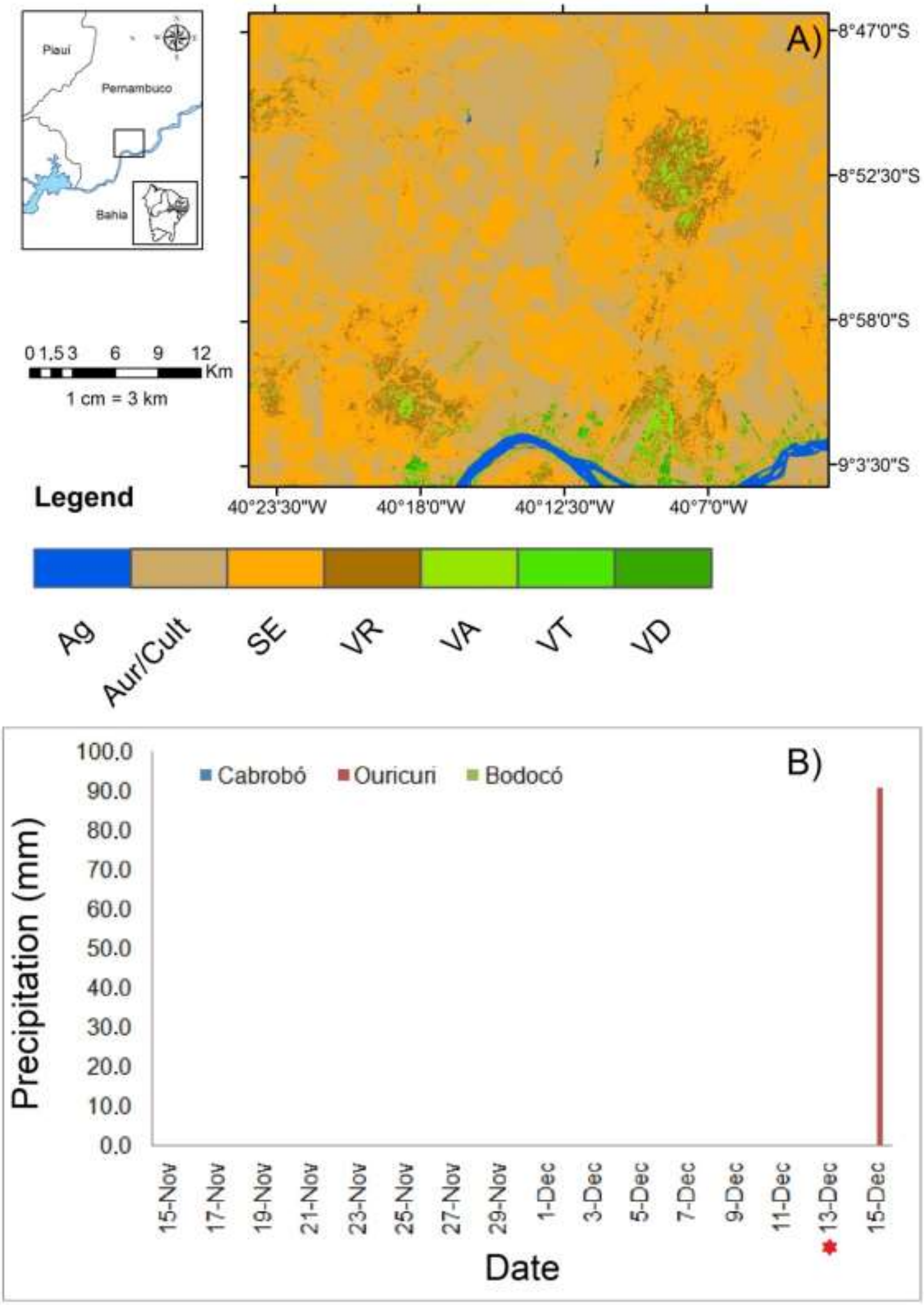

Figure 7. Thematic map of land cover for the study area. according to the NDVI for each pixel of the day Dec.13.2003 (A). associated with the distribution of rainfall during the period from November 15 to December 15. 2003 (B) for semiarid of the Pernambuco state.

Gurgel et al. (2003) studied variability of NDVI in Brazil. confirmed a high correlation between the variable rainfall and NDVI. Despite the Caatinga biome with elevated be considered a weakness. has a high power of resilience due to the formation of biomass occur almost immediately after rain events. The behavior of the semiarid vegetation in response to rainfall was also observed by Barbosa et al. (2006). which showed the resilience of the vegetation (release) during rainy periods.

4. Conclusions

The vegetation coverage proved resilient high power in relation to rainfall. with higher intakes in vegetation cover. in 1996. NDVI.

The rainy season coincides with higher values of the index Normalized Difference Vegetation and lower albedo.

The temporal variability of precipitation was represented by four components which explained about 64% of data variance.

The data presented NDVI of two main components responsible for explaining more than 70% of the spatio-temporal.

The techniques of image processing techniques associated satellites principal component analysis (PCA) were efficient in the study of spatio-temporal variability of surface and meteorological data. respectively.

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