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Spectral trend of vegetation with rainfall in events of El Niño-Southern Oscillation for Atlantic Forest biome, Brazil

Thais Cristina de Oliveira Souza · Rafael Coll Delgado · Iris Cristiane Magistrali · Gilsonley Lopes dos Santos · Daniel Costa de Carvalho · Paulo Eduardo Teodoro · Carlos Antônio da Silva Júnior · Rodrigo Hotzz Caúla

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Abstract This study aimed to analyze the spectral trend of vegetation with rainfall in El Niño-Southern Oscillation events (ENSO) in the Atlantic Forest, Brazil. Monthly rainfall data were collected from 85 conventional meteorological stations (EMC), data from the Enhanced Vegetation Index 2 (EVI2) and ENSO events (*El Niño*, *La Niña*, and Neutral) in the period from 2001 to 2013. Afterwards, state cluster analysis was performed using the results of non-parametric tests. The Mann-Kendall (MK) non-parametric test did not identify a trend pattern in rainfall distribution in the Atlantic Forest. The results for EVI2 by state and region showed that the trend is decreasing in the Northeast Region, except for the states of Alagoas and Pernambuco. Southeast region showed an increasing trend of EVI2 (except for Rio de Janeiro and São Paulo), while the South region showed a decreasing trend. In the Midwest, the trend was significantly decreasing. In the prognosis elaborated for the future, the regions with significant declines of the vegetation were the Northeast and Midwest. This study shows that the Atlantic Forest in some regions of Brazil has been suffering from the growing urbanization process and there is a trend of soil degradation.

T. C. de Oliveira Souza · R. C. Delgado · I. C. Magistrali · G. L. dos Santos · D. C. de Carvalho · R. H. Caúla
Federal Rural University of Rio de Janeiro (UFRRJ), Seropédica, Rio de Janeiro 23890-000, Brazil

P. E. Teodoro (✉)
Federal University of Mato Grosso do Sul (UFMS), Chapadão do Sul, Mato Grosso do Sul 79560-000, Brazil
e-mail: eduteodoro@hotmail.com

C. A. da Silva Júnior
State University of Mato Grosso (UNEMAT), Alta Floresta, Mato Grosso 78160-000, Brazil

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Introduction

World's tropical forests, after centuries of exploitation and millions of deforested hectares, now have large areas converted into pastures, crops, and urban centers (Fialho and Zinn 2014; Caúla et al. 2015, 2016). In Brazil, the Atlantic Forest biome has only 7% of its original territory, and although it is very fragmented, it still has great social and environmental importance (Varjabedian 2010). These fragments of secondary and primitive vegetation are important targets of research, in which we seek to know the vegetation dynamics and the positive influence of cities and/or states: regulation and maintenance of the various microclimates, a solution for environmental mitigation (Salata et al. 2017; Grifoni et al. 2017), change in landscape due to urbanization in forested areas, ecological restoration, and carbon sequestration (Fialho and Zinn 2014; Goulart et al. 2015; Nunes et al. 2015).

Despite its importance, it is one of the biodiversity richest and most endangered areas of the planet, being declared Biosphere Reserve by Unesco, and National Patrimony, by the Federal Constitution of 1988, in addition to being one of the World Hotspots (SOS MATA ATLÂNTICA 2017). It is estimated that in the Atlantic Forest, there are about 20,000 plant species (about 35% of the species in the Brazilian Atlantic Forest), including several endemic and endangered species. Regarding the fauna, the surveys already carried out indicate that it has 849 species of birds, 370 species of amphibians, 200 species of reptiles, 270 of mammals, and about 350 species of fish, and even influence the Pantanal Biome (MMA- Ministério do Meio Ambiente 2017a, b). The importance of this biome is so great that Federal Law No. 11,428/2006, known as the Atlantic Forest Law, regulates the conservation, protection, regeneration, and utilization of the Atlantic Forest, and Decree No. 6.660/2008, details "what", "how", and "where" there may be intervention or sustainable use of native vegetation (MMA- Ministério do Meio Ambiente 2017a, b).

Considering the need for vegetation evaluation in large areas, Huete et al. (1997) developed the Enhanced Vegetation Index (EVI), widely used in the study of vegetation dynamics (Silva Junior et al. 2014). Its main objective is to decrease the soil and atmosphere effect on the analysis of vegetation dynamics with the use of biomass. For example, Zucca et al. (2015) evaluated the biomass production from eight vegetation indices in the study of desertification in Morocco, with emphasis on EVI and *Soil Adjusted Vegetation Index* (SAVI—Huete 1988) in comparison to the others. The EVI was formulated from the combination of the SAVI and *Atmosphere Resistant Vegetation Index* (ARVI) (Kaufman and Tanre 1992). Due to the reduction of the canopy substrate effects and the influence of the atmosphere, EVI allows monitoring of vegetation, since it is an index that enhances the vegetation signal by optimizing the sensitivity in regions with high biomass values (Jiang et al. 2008; Mondal 2011). According to Gao et al. (2000), the EVI has a better response of the canopy structural variations, including the Leaf Area Index (LAI), the type and architecture of the canopy, and the vegetation phyto-physiognomy.

On the other hand, EVI2, an EVI version, is used with images of sensors not having the blue band (such as the ResourceSat series), calibrated to present similar results to EVI (Jiang et al. 2008). Several temporal spectra of vegetation studies with EVI2 were carried out in Brazil, mainly for the spectral and temporal characterization of pastures in the Triângulo Mineiro, Minas Gerais (Anjos et al. 2013), for the relationship between vegetation indices and carbon dioxide (CO_2) in two environments in the Amazon region (Da Silva and Baptista 2015). In a study using images from *Advanced Very High Resolution Radiometer* (AVHRR) for global reconstruction of vegetation data, Zhang (2015) used data from EVI2, since data from the *Normalized Vegetation Index* (NDVI) are sensitive to the effects of soil brightness and attenuation and scattering of atmospheric aerosols.

In addition to this spectral information, vegetation indices undergo changes due to climatic factors and can be correlated with meteorological variables such as rainfall and air temperature (Delgado et al. 2012; Goulart et al. 2015; Nunes et al. 2015). Biodiversity loss due to anthropic reasons followed by major episodes of forest fires, burnings, and extreme droughts has been implicated in devastating consequences for forest systems on a regional and global scale, economic losses, and an increase in social problems (Martín et al. 2012; Jacob et al. 2015; Caúla et al. 2015, 2016).

Climatic anomalies such as the ENSO phenomenon (El Niño-Southern Oscillation) have been worrying the scientific community at global and regional level (Tekleab et al. 2013; Park et al. 2014), being the most important the ocean-atmosphere coupling with action around the planet (Cai et al. 2015). Some studies show the ENSO influence on biological feedbacks and biogeochemical processes (Park et al. 2014), spatial and temporal variability of rainfall in many parts of the world (Duhan and Pandey 2013; Debortoli et al. 2015), hydrological time series (Rougé et al. 2013; Goyal 2014), and hydroclimatic trends (Tekleab et al. 2013).

In the last decades, few studies have been done relating the vegetation pattern to rainfall (Poveda et al. 2011; Goulart et al. 2015), followed by the ENSO influence on the Brazilian Atlantic Forest, especially at regional and state scales. Therefore, the objective of this study is to analyze the spectral trend of vegetation with rainfall in ENSO events (El Niño, La Niña, and Neutral) in the Atlantic Forest biome, Brazil.

Material and methods

Study area

Study area comprises the Atlantic Forest biome (Fig. 1), formed by large areas of native vegetation, with Deciduous Seasonal Forest, Semi-deciduous Seasonal Forest,

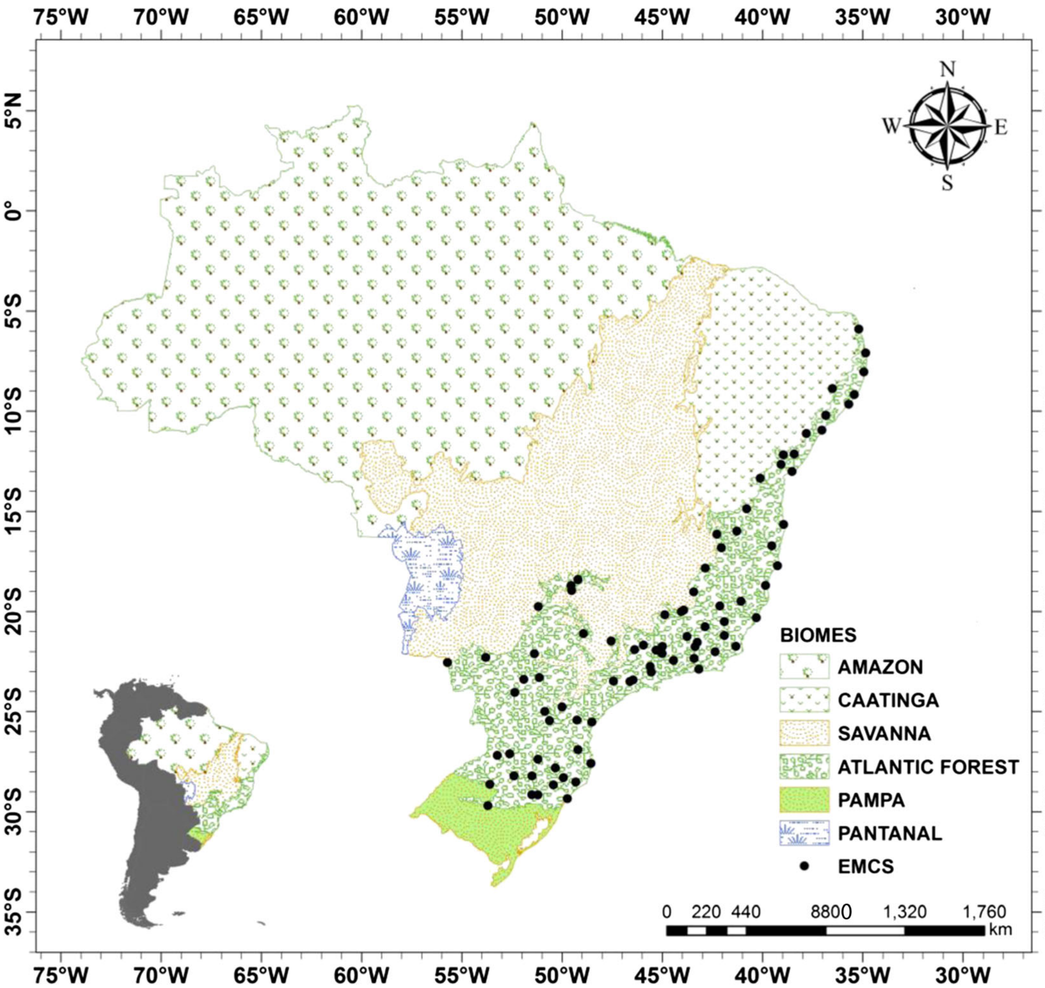

Fig. 1 Geographic location of the study area highlighting the Atlantic Forest biome, with emphasis on other biomes (Amazon, Caatinga, Pampa, Savanna, and Pantanal) and Conventional Weather Stations (EMCS)

Dense Ombrophylous Forest, Open Ombrophylous Forest, Mixed Ombrophylous Forest, and associated ecosystems such as sandbanks (restingas), mangroves, and altitude fields. Originally, vegetation extended by approximately 1,300,000 km^2 in 17 Brazilian states (from Ceará to Rio Grande do Sul, all east coast). Currently, remainder is reduced to about 22% (286,000 km^2) of the original cover, with different stages of regeneration. Of this total, only 7% are well preserved in fragments above 100 ha (MMA- Ministério do Meio Ambiente 2017a, b).

Climate

According to Köppen, the climate in the Atlantic Forest region is predominantly tropical humid (Peel et al. 2007). This generalization occurs due to the proximity of the ocean, regional atmospheric dynamics, and topographic diversity. However, in geographic, physical, and climatic terms, Atlantic Forest, thus defined, presents a large latitudinal, longitudinal, altitudinal, and climatic range. It extends from 30° South latitude to around 30°, remaining relatively restricted to the coast in its northernmost portion and internalizing more than 800 km of the coast near its southern limit. It is also distributed by an altitudinal gradient from sea level to about 3000 m of altitude, reaching the summit of some of the highest mountain ranges in Brazil (Alvares et al. 2013). Because of this geographic and physical heterogeneity, the Atlantic meets from location that holds the record of lower temperature in Brazil to areas with an average annual temperature above 25 °C, and this range of values is also observed in rainfall differences between different regions (IBGE – Instituto Brasileiro de Geografia e Estatística 2010; Lima 2013).

Rainfall data and ENSO events

Monthly rainfall data from 2001 to 2013 were obtained from the National Institute of Meteorology/Meteorological Data Bank for Teaching and Research-INMET/BDMEP (BDMEP - Banco de dados Meteorológicos para Ensino e Pesquisa 2017), of 85 conventional meteorological stations (EMC) located along the Atlantic Forest biome (Fig. 1).

Information on the occurrence of ENSO was obtained from the National Oceanic and Atmospheric Administration/Climate Prediction Center-NOAA/CPC (NOAA/CPC - National Oceanic and Atmospheric Administration/Climate Prediction Center 2017). Table 1 shows El Niño, La Niña, and Neutral years from 2001 to 2013, classified as warm (red) and cold (blue), based on a range ± 5 °C of the sea surface temperature (SST) (NOAA/CPC - National Oceanic and Atmospheric Administration/Climate Prediction Center 2017).

Many indices have been proposed in the literature to describe ENSO, e.g., the Bivariate El Niño-Southern Oscillation (Cañón et al. 2007), the Cold Tongue Index (Wolter and Timlin 2011), the Southern Oscillation Index, and the Multivariate ENSO Index–MEI (Wolter 1987), which is based on six meteorological variables measured over the tropical Pacific. These six variables are sea-level pressure, zonal and meridional components of the surface wind, sea surface temperature, surface air temperature, and total cloudiness fraction of the sky. The period was considered an El-Niño year when MEI was higher than + 0.5 for six consecutive months. Conversely, a La-Niña year was assumed when MEI was lower than − 0.5 for more than 6 months. If MEI was within ± 0.5 for more than 6 months, the year was considered neutral (Rasmusson and Carpenter 1982; Cañón et al. 2007; Wolter and Timlin 2011).

Time series obtained from LAF-INPE of the EVI2 (2001–2013)

Monthly time series of EVI2 was similar to the rainfall series for comparison purposes. The methodology adopted is similar to Jiang et al. (2008) of the Laboratory of Remote Sensing Applied to Agriculture and Forest of the National Institute of Space Research (LAF-INPE), available at the electronic address: <https://www.dsr.inpe.br/laf/series/index.php>. Further information can be found in Freitas et al.

Table 1 Index Niño in the Pacific Ocean over the evaluated years

ENSO	DJF	JFM	FMA	MAM	AMJ	MJJ	JJA	JAS	ASO	SON	OND	NDJ
2001	**-0.7**	**-0.6**	**-0.5**	-0.3	-0.2	-0.1	0	-0.1	-0.1	-0.2	-0.3	-0.3
2002	-0.2	-0.1	0.1	0.2	0.4	**0.7**	**0.8**	**0.9**	**1**	**1.2**	**1.3**	**1.1**
2003	**0.9**	**0.6**	0.4	0	-0.2	-0.1	0.1	0.2	0.3	0.4	0.4	0.4
2004	0.3	0.2	0.1	0.1	0.2	0.3	**0.5**	**0.7**	**0.7**	**0.7**	**0.7**	**0.7**
2005	**0.6**	**0.6**	**0.5**	**0.5**	0.4	0.2	0.1	0	0	-0.1	-0.4	-0.7
2006	-0.7	-0.6	-0.4	-0.2	0	0.1	0.2	0.3	**0.5**	**0.8**	**0.9**	**1**
2007	**0.7**	0.3	0	-0.1	-0.2	-0.2	-0.3	**-0.6**	**-0.8**	**-1.1**	**-1.2**	**-1.3**
2008	**-1.4**	**-1.3**	**-1.1**	**-0.9**	**-0.7**	**-0.5**	-0.3	-0.2	-0.2	-0.3	-0.5	-0.7
2009	-0.8	-0.7	-0.4	-0.1	0.2	0.4	**0.5**	**0.6**	**0.7**	**1**	**1.2**	**1.3**
2010	**1.3**	**1.1**	**0.8**	**0.5**	0	-0.4	**-0.8**	**-1.1**	**-1.3**	**-1.4**	**-1.3**	**-1.4**
2011	**-1.3**	**-1.1**	**-0.8**	**-0.6**	-0.3	-0.2	-0.3	**-0.5**	**-0.7**	**-0.9**	**-0.9**	**-0.8**
2012	**-0.7**	**-0.6**	**-0.5**	-0.4	-0.3	-0.1	0.1	0.3	0.4	0.4	0.2	-0.2
2013	-0.4	-0.5	-0.3	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.2	-0.3

Source: National Oceanic and Atmospheric Administration/Climate Prediction Center; the abbreviations DJF, JFM, ..., NDJ refer to three overlapping months, i.e., DJF: December, January, and February; values in blue characterize La Niña occurrence; blank values characterize neutrality; values in red characterize El Niño occurrence

(2011). The LAF-INPE files were obtained in *.csv* format. Thus, they were treated and organized vectorially for the Atlantic Forest biome.

The calculation of EVI2 is given by

$$EVI2 = G\frac{IVP-V}{IVP+\left(6-7,{}^{5}/_{c}\right)V+1}EVI2 = G\left[\frac{NIR-R}{NIR+\left(6^{-7.5}/_{c}\right)R+1}\right] \quad (1)$$

wherein

NIR near infrared (μm);
R red (μm);
G gain factor equal to 2.5;
C coefficient of correction of atmospheric effects equal to VA^{-1}.

In the study, EVI2 was applied, which is able to easily identify the replacement of land cover by other types of cover (Jiang et al. 2008), being obtained from January 2001 to December 2013.

Statistical analysis of data

Mann-Kendall and Pettitt non-parametric tests

According to the methodology described by Caúla et al. (2016), analysis of annual rainfall trend and EVI2 from 2001 to 2013 by regions inserted in the Atlantic Forest Biome in Brazil was performed. Considering the total monthly rainfall data and monthly mean values of EVI2 for the same series, both were submitted to the Mann-Kendall (MK) non-parametric test. This test (Mann 1945; Kendall, 1975) considers that, in the case of stability of a time series, the succession of values occurs independently and the probability distribution must always remain the same (random series).

Based on the Z statistics analysis, a decision can be taken to accept or reject Ho, i.e., we can confirm the hypothesis of data stability or reject it in favor of the alternative hypothesis (existence of trend in the data). The Z statistics sign indicates whether the trend is increasing ($Z > 0$) or decreasing ($Z < 0$). The α significance level adopted is $\alpha = 0.05 = 5\%$ for the MK test. If the probability p of the MK test is less than the α level, $p < \alpha$, a statistically significant trend exists, whereas a $p > \alpha$ confirms an insignificant trend. For samples where there are no trends, the Z value is close to zero (Mann 1945; Kendall, 1975; Caúla et al. 2016).

Monthly rainfall and EVI2 data were submitted to the Pettitt test (Pettitt 1979; Wanderley et al. 2013; Caúla et al. 2016), which uses a version of the Mann-Whitney test, in which it is verified that two samples X1, ... Xt and Xt + 1,..., XT are from the same population. The Ut, T statistics counts the number of times a member of the first sample is larger than the member of the second. This statistic finds the point at which a sudden change occurred in the mean of a time series.

Markov chain

In this study, for predicting the vegetation state of the Atlantic Forest biome for the next 10 years, we used the Markov Chain processed in software R version 3.2.1, by using the CS (Curvature Sen, %)—of EVI2 obtained in the Mann-Kendall test whose data were left in module and clustered by region.

This prognosis was carried out from the study of the forest cover condition from 2001 to 2013, which is considered as the starting point, or year "0". From this analysis and prognosis, the forest cover status was predicted for the next 10 years, according to Table 2.

With application in several areas of knowledge, Markov Chain is represented by the following general equation:

$$\prod(t+1) = p^{n}\prod^{t} \quad (2)$$

wherein $\prod(t+1)$ is the state after time t, $\prod(t)$ is the state at time t, and pn is the possible states to happen.

As the Markov Chain works by multiplying a 1×2 matrix (state in evidence) by a 2×2 matrix (two other states), to compare all the states among each other, several scenarios have been proposed.

They were built graphics boxplots and distribution of EVI2 values over the years that were characterized by the occurrence of El Niño and La Niña along the Brazilian regions of occurrence of the Atlantic Forest. $\Pi(t+1) = p^{n}\Pi^{t}$ Subsequently, the cluster analysis by EVI2 states was applied using Euclidian mean distance and Ward method for clustering. Multiple regression analysis was applied to the total data set for ENSO, rainfall, and vegetation (dependent variable), to evaluate the spatial dependence of the time series on the Atlantic Forest biome.

Table 2 Year prognosis of the Markov Chain by regions of the Atlantic Forest biome

0	1	2	3	4	5	6	7	8	9	10
2001–2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023

Statistical analysis and maps were performed in software ArcGIS version 10.5 and R version 3.2.1 (R Development Core Team 2011) using the packages "trend", "markovchain", and "ggplot2".

Results

Northeast region

In the MK analysis in the Northeast region, it was verified that the trend is a decrease of the forest cover with mean values of MK (− 0.085) (Table 3), except Alagoas and Pernambuco, where the trend is for forest cover growth (MK = 0.025). There is a marked fall in vegetation mainly in the year 2013 (Fig. 2), being the mean values of EVI2 over the months and years studied 0.42. Pettitt test (Table 3) showed sudden trend changes for Rio Grande do Norte in August 2005, Paraíba in August 2006, Alagoas in March 2005, Pernambuco in April 2013, Sergipe in October 2004, and Bahia in April 2008. The most significant seasons for the test were winter and autumn, which accounted for 33.33% of the series. This region did not present significance with El Niño events, since only 2004 and 2005 were characterized as weak El Niño (Table 1). La Niña and Neutrality events were significant according to the Pettitt test (2006, 2008, and 2013) (Table 1). In the Markov chain analysis for present and future EVI2 events, there is a significant increase in vegetation over time with CS (%) of approximately 3% in year 3 (Fig. 3), but after this year, there is a significant reduction of 0.14% in the year 10, the decreasing over time is significant.

Southeast region

Unlike the Northeast, the states of the Southeast region, except Rio de Janeiro and São Paulo, presented a trend of vegetation growth (Table 3), with a mean value of EVI2 higher than the Northeast region of 0.45 (Fig. 2). Rio de Janeiro and São Paulo show a non-significant and

Table 3 Results obtained from the Mann-Kendall tests (Z score, *p* value, curvature sen-CS, CS%, and MK) and Pettitt (month and year) for EVI2 in the Atlantic Forest biome by regions/states (FU)

Region	Estate	*Z* score	*P* value	CS	*P* value	CS %	MK	*P* value	Pettitt	
									Month	Year
Northeast	RN	− 2.22	0.03	0.00	0.03	− 0.10	− 0.11	0.03	August	2005
	PB	− 1.33	0.18	0.00	0.18	− 0.04	− 0.07	0.18	August	2006
	AL	0.58	0.56	0.00	0.56	0.02	0.03	0.56	March	2005
	PE	0.36	0.72	0.00	0.72	0.01	0.02	0.72	April	2013
	SE	− 2.47	0.01	0.00	0.01	− 0.07	− 0.12	0.01	October	2004
	BA	− 0.75	0.45	0.00	0.45	− 0.02	− 0.04	0.45	April	2008
Southeast	MG	0.50	0.62	0.00	0.62	0.02	0.03	0.62	December	2003
	ES	0.50	0.62	0.00	0.62	0.02	0.03	0.62	April	2003
	RJ	− 0.30	0.77	0.00	0.77	− 0.01	− 0.02	0.77	July	2004
	SP	8.28	0.00	0.00	0.00	0.27	− 0.42	0.00	August	2006
South	PR	− 2.34	0.02	0.00	0.02	− 0.06	− 0.12	0.02	March	2007
	SC	− 1.01	0.31	0.00	0.31	− 0.03	− 0.05	0.31	April	2004
	RS	− 0.41	0.68	0.00	0.68	− 0.01	− 0.02	0.68	March	2008
Midwest	MS	− 0.41	0.68	0.00	0.68	− 0.01	− 0.02	0.68	June	2002
	GO	0.41	0.00	0.00	0.00	0.27	− 0.21	0.00	October	2008

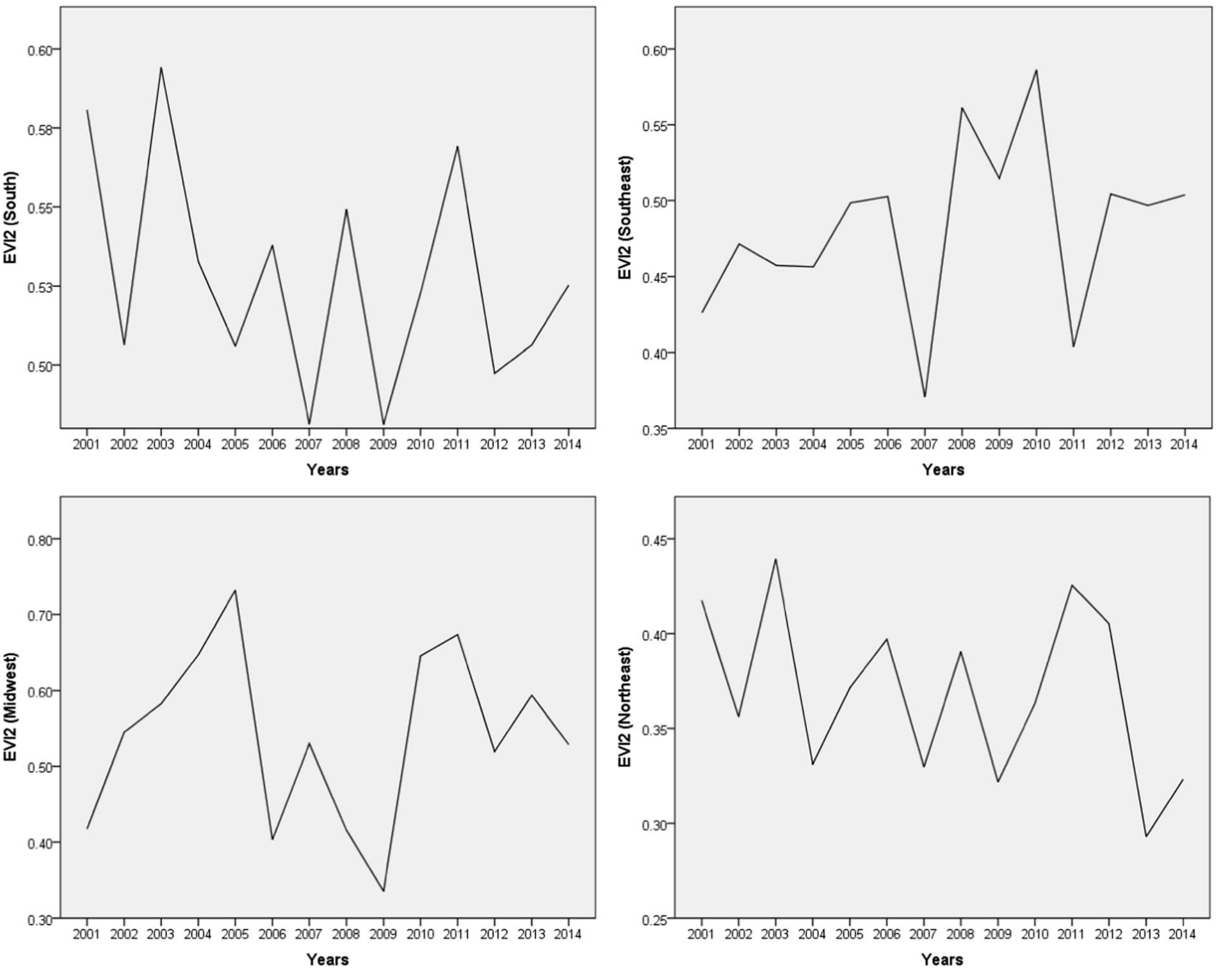

Fig. 2 Distribution of EVI2 index by regions of Brazil in the Atlantic Forest biome among 2001 and 2014

significant downward trend in forest cover (MK = − 0.02 and − 0.42). In the analysis of the changes, the Pettitt test proved to be significant for this region in December 2003, April 2003, July 2004, and August 2006. Weak El Niño and Neutrality events act more on this region; on the other hand, La Niña had no significance in the Southeast. During the year considered "0" up to year 4, the stabilization of CS% (0.02%) occurred; from this year, there was a decreased CS%, which indicates decrease in EVI2 series until year 8 (Fig. 3).

South region

In the South, the three states presented a decreasing trend of the vegetation cover index in the studied period (Table 3), especially Paraná (− 0.12), which presents a significant trend, unlike Santa Catarina (− 0.05) and Rio Grande do Sul (− 0.02). The mean EVI2 for the South region was 0.40, lower than the Northeast and Southeast regions (Fig. 2). The most abrupt years and months for the Pettitt test were April 2004 (Santa Catarina), March 2007 (Paraná), and April 2008 in Rio Grande do Sul. Autumn season was the one that presented 100% in the Pettitt test for Southern region of the country. El Niño, La Niña, and Neutrality were significant for this region, which results in a distinct balance of these phenomena in the southern Brazil. From year 0, there is a growth of 0.08% of CS up to year 2; after this year, there is a stability of CS, but with slight vegetation decline until the year 10 (Fig. 3).

Midwest region

It is verified that in Mato Grosso do Sul, there is no significant downward trend in forest cover (− 0.02),

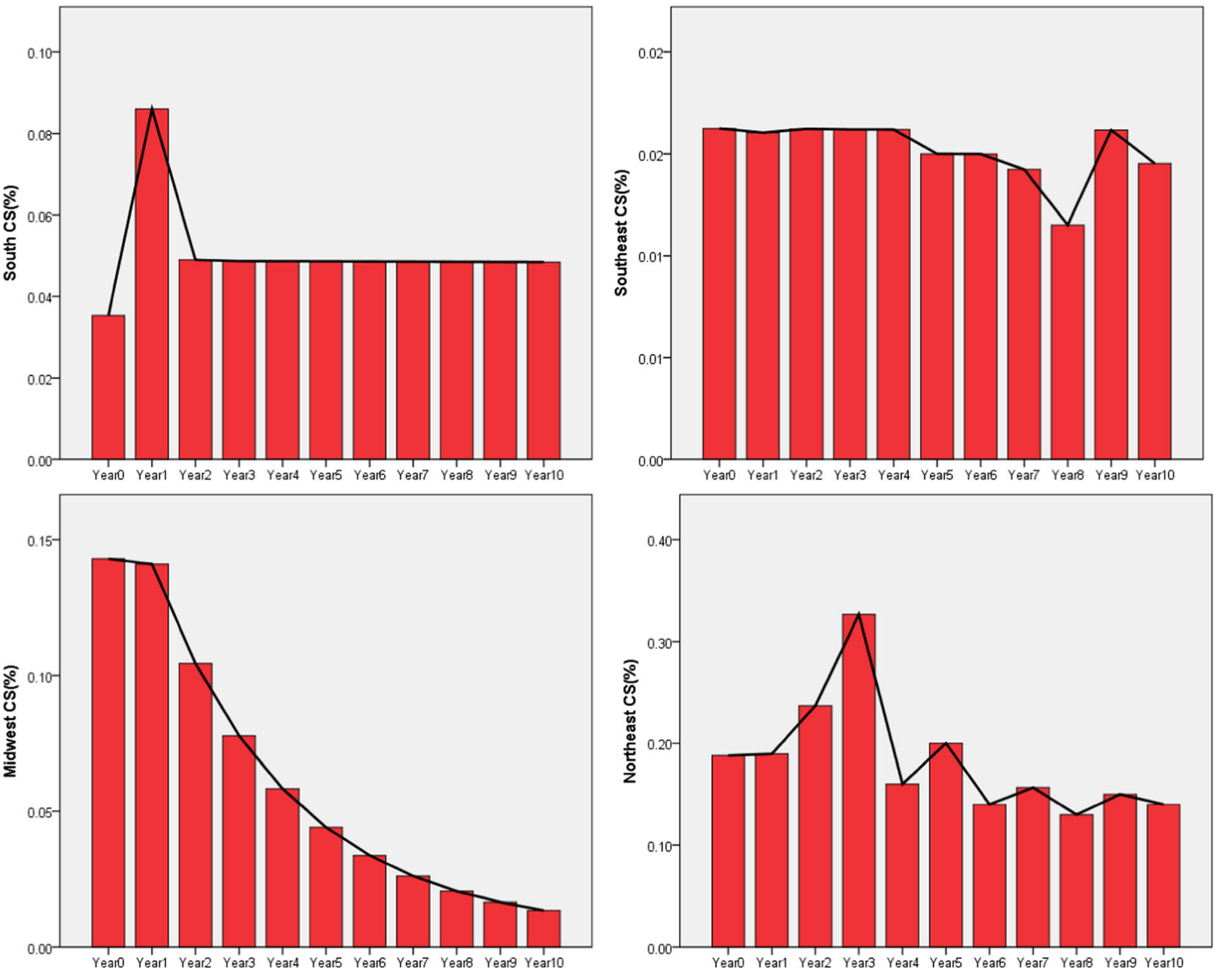

Fig. 3 Ten-year prognosis of the curvature sen (CS, %) behavior of the regions of Brazil covering the Atlantic Forest biome

while in the state of Goiás, it is significantly increasing (− 0.21) (Table 3). In the Pettitt analysis, June 2002 and October 2008 were highlights for Mato Grosso do Sul and Goiás, respectively. There was a balance between the extremely strong El Niño and extremely strong La Niña in 2008 in the Midwest region. Decreasing is significant over the years with CS value in year 0 of 0.15% and reaching a minimum of 0.01% in year 10 (2023) (Fig. 4).

Multiple linear regression applied to EVI2, vegetation, and rainfall in ENSO events

Table 4 presents statistical information of the multiple regression applied to EVI2 values as a function of rainfall and vegetation for the years of ENSO in around biome. There was a significant effect of the model tested for the years 2007, 2010, 2011, and 2012. Estimates of the coefficient of determination ranged from 69 to 93% for these cases. In El Niño years, there was a significant effect of multiple regression for all years, with the exception of 2002. In general, estimates of the coefficient of determination of the model tested were higher in El Niño years.

Descriptive and cluster analysis of EVI2 and states containing the Atlantic Forest biome

The descriptive analysis applied to EVI2 values over the years is contained in Fig. 4. It is possible to verify that EVI2 values in El Niño years were slightly higher than EVI2 values in La Niña years. Independent of the ENSO events, the Midwest presented the highest mean EVI2 over the years, followed by the Southeast region. The South and Northeast regions presented similar averages over the years. By cluster analysis (Fig. 5) applied to the

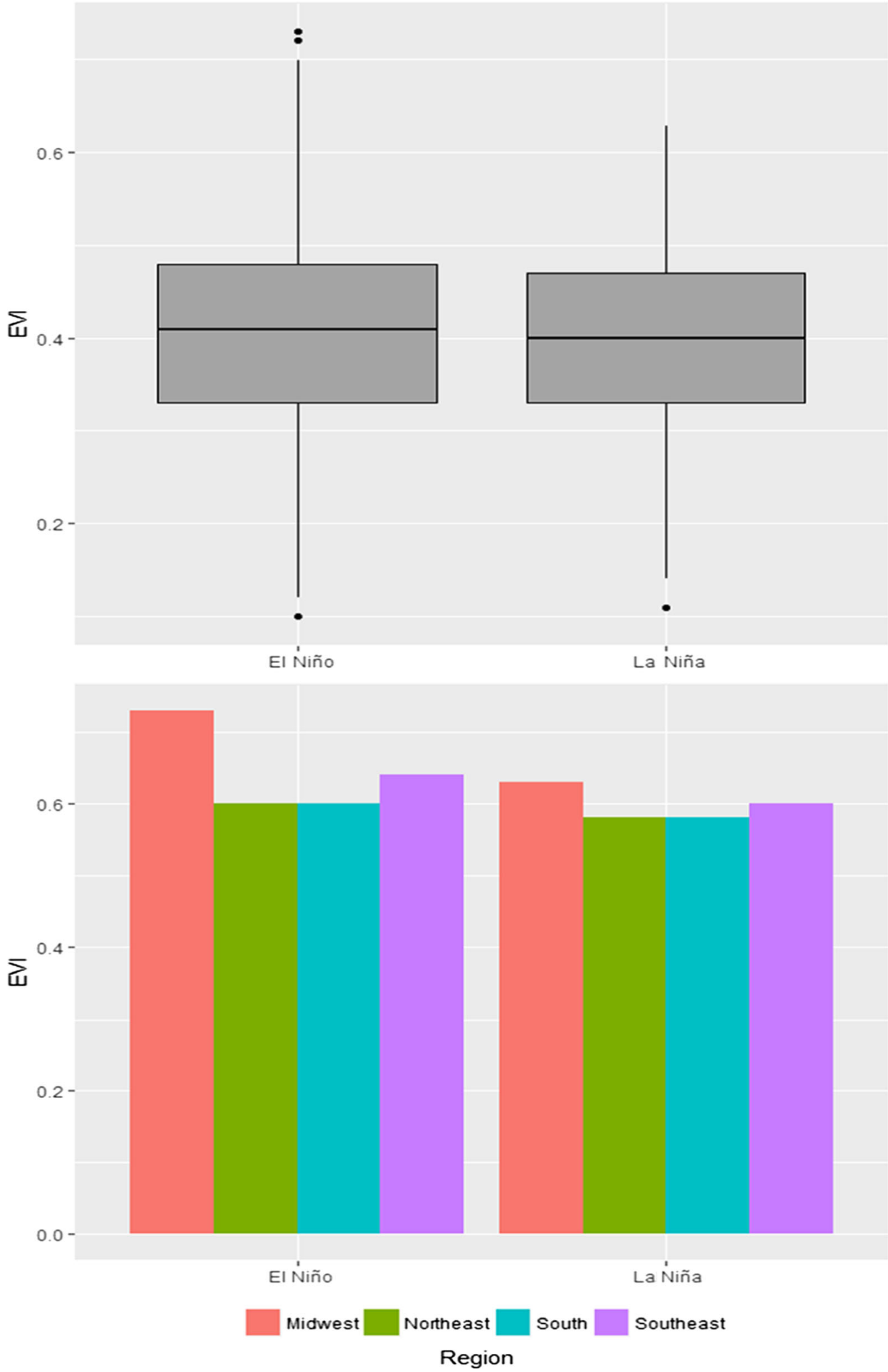

Fig. 4 Boxplot (**a**) and distribution (**b**) of EVI2 values of Brazilian regions in ENSO events

Table 4 Multiple regression of EVI2 values as a function of vegetation and rainfall for the years of ENSO events highlighting R^2 index and regression coefficients

Years	Rainfall	Vegetation		Years	Rainfall	Vegetation	
La Niña	β_1	β_2	R^2	El Niño	β_1	β_2	R^2
2001	31.16	565.57	0.27^{ns}	2002	− 197.73	1024.23	0.45^{ns}
2007	− 211.66	1030.59	0.69*	2003	1222.85	− 1826.50	0.99*
2008	− 342.09	1297.13	0.47^{ns}	2004	− 452.93	1615.69	0.69*
2010	− 328.74	1405.17	0.67*	2005	− 712.19	2097.18	0.76*
2011	− 282.58	1260.01	0.72*	2006	− 431.85	1606.26	0.89*
2012	− 2650.66	6033.50	0.93*	2009	− 195.29	900.87	0.63*
				2010	− 1423.58	3642.19	0.51*

^{ns} and * not significant and significant at 5% probability by *t* test

results of the non-parametric tests of EVI2, there was a formation of four homogeneous groups. The G1 group was formed by the states of São Paulo (SP) and Goiás (GO). The group G_2 was composed by Paraná (PR), Rio Grande do Norte (RN), and Sergipe (SE). The states of Alagoas (AL), Pernambuco (PE), Minas Gerais (MG), and Espírito Santo (ES) presented an insignificant increasing trend, forming the group G_3. The group G_4 was composed of the states that presented insignificant decreasing trend for the vegetation: Rio Grande do Sul (RS), Mato Grosso do Sul (MS), Paraíba (PB), Bahia (BA), Rio de Janeiro (RJ), and Santa Catarina (SC).

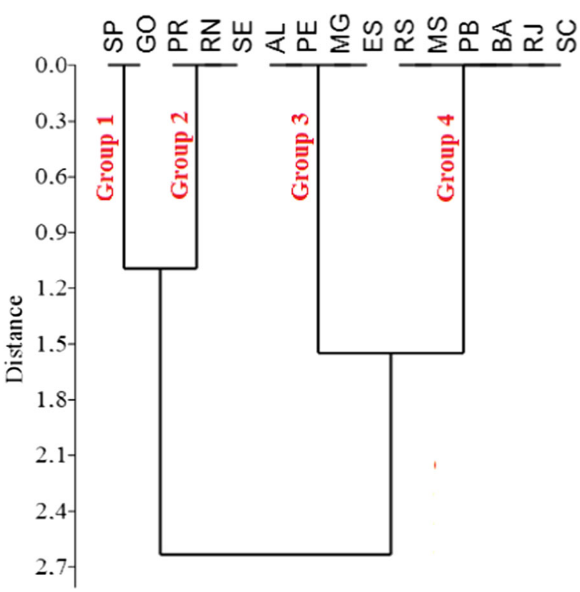

Fig. 5 Cluster of states (dendrogram) for the values of the Mann-Kendall and Pettitt statistical tests for the EVI2 index in the Atlantic Forest biome

Discussion

High correlations found in this study with the ENSO events are always associated in the same period, because depending on their phase (*El Niño* or *La Niña*), they induce scarcity or abundance of rainfall (Jong et al. 2016). Other works in other biomes also emphasized the importance of the rainfall correlation with significant events such as El Niño and La Niña (Capozzoli et al. 2017).

Besides the rainfall correlation with ENSO events found in this study for the Atlantic Forest biome, other researchers correlate these events with the anomalous emergence of hotspots (Yocom Kent et al. 2017; Santos et al. 2017a, b). The results found with significant vegetation decreasing over the studied period may be associated to a higher amount of fires in some regions of Brazil. Caúla et al. (2016) observed that most of the hotspots occurred in the Northern Fluminense Region, of the State of Rio de Janeiro, in the municipality of Campos dos Goytacazes (72%). It was still possible to conclude that among the land use and land cover classes, the pasture class was the one with the highest amount of foci and related to the hotspots, occurring increase in the studied period. Given the changes in the climate, geopolitical units of high demography inserted in priority conservation areas such as the Brazilian Southeastern States and the Atlantic Forest biomes, respectively, present a great vulnerability to these climatic changes as well as less capacity to adapt to a new reality (Ferreira 2016).

In some years, with emphasis on 2001 and 2002 (La Niña and El Niño), there was no direct relationship between rainfall and vegetation growth. Some studies in other regions (Tomasella et al. 2013; Salgueiro et al., 2016; Marengo and Espinoza 2016; Santos et al. 2017a,

b) emphasize the importance of the geographical position of the study region and that the Atlantic Dipole and other small and large-scale phenomena may be more significant in increasing or decreasing rainfall than ENSO. The decline in vegetation over the period studied for the Atlantic Forest in some regions is consistent with the various studies on deforestation, fauna, and endangered species in Brazil (Gouveia et al. 2016; Santana et al. 2016). This biome is considered an area extremely subject to desertification, not only by deforestation and land use change, but also, and mainly, by climatic and anthropogenic conditions. In addition, the Atlantic Forest biome has been exploited and destroyed for over 500 years, being replaced first by sugarcane (sixteenth century), and by cacao plantations in Bahia (twentieth century). It should be noted that the Southeast region was also target of exploitation throughout the centuries, with emphasis on the coffee cultivation in Rio de Janeiro and São Paulo (eighteenth and nineteenth century), as well as livestock in São Paulo and Minas Gerais (nineteenth and twentieth centuries) (Colombo and Joly 2010).

Results found in the future projection of the Atlantic Forest in the Southeast region and in other regions of the country are worrisome, since urban growth is increasing every decade (Silva et al. 2017). It should be noted that this situation is serious, since in the area of the Atlantic Forest biome about 70% of the Brazilian population (120 million people), responsible for 80% of the country's Gross Domestic Product (GDP) (MMA-Ministério do Meio Ambiente 2017a, b). Considering the climate change predicted by the International Panel on Climate Change (IPCC - Intergovernmental Panel on Climate Change 2017), it is important to consider the increasingly frequent occurrence of extreme climatic events, such as great droughts.

In the Atlantic Forest biome, the differentiation between rain forests and semi-deciduous forests is strongly correlated with the rainfall regime of these areas (Oliveira-Filho and Fontes 2000). Through these values, it was observed that the Atlantic Forest biome responds better to El Niño events, resulting in a higher correlation with rainfall. In this sense, variations in the rainfall regime, seasonality among other factors such as temperature and distance of the ocean are important variables to be considered in works in the Atlantic Forest and can help in understanding of species distribution patterns.

The G2 (PR, RN, and SE) states presented a significant decrease in forest cover over the time series. The other groups (G3 and G4) allocated states with a tendency to increase and insignificant decrease. These results are important from the point of view of public policies, since government actions can be applied to places where the decline of the Atlantic Forest biome area has occurred. On the other hand, where there is an increase of the area of this biome, new governmental programs can be created to avoid the illegal deforestation of such areas.

Conclusions

In the Northeast, South, and Center-West regions of Brazil, there is decreasing forest cover trend, exceptions are the states of Alagoas and Pernambuco, with an insignificant increase trend. The Southeast region has an increase trend in Espírito Santo and Minas Gerais, except for Rio de Janeiro and São Paulo, which showed a significant decreasing trend. Making the prognosis of the state of vegetation for 10 years, we verified that the situation is critical for both regions with emphasis the Midwest region of the country.

The Atlantic Forest biome responds better to El Niño events, which results in a greater correlation with rainfall.

Given the above, the need for research related to monitoring and prediction of areas susceptible to desertification mainly of the Atlantic Forest is evident. However, for carrying out such research, there is need for representative regions and that have a robust database for analysis.

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