UNIVERSIDADE FEDERAL DE PERNAMBUCO
CENTRO DE TECNOLOGIA E GEOCIÊNCIAS
DEPARTAMENTO DE ENGENHARIA CARTOGRÁFICA
PROGRAMA DE PÓS-GRADUAÇÃO EM CIÊNCIAS GEODÉSICAS E TECNOLOGIAS DA GEOINFORMAÇÃO

INESSA RACINE GOMES DE ARAÚJO

DETECTION OF AGRICULTURAL DROUGHT IMPACTS ON SOYBEANS PRODUCTION IN BRAZIL (1983-2016) USING PRECIPITATION ANOMALIES, NDVI AND ESPI

Recife
2019

INESSA RACINE GOMES DE ARAÚJO

DETECTION OF AGRICULTURAL DROUGHT IMPACTS ON SOYBEANS PRODUCTION IN BRAZIL (1983-2016) USING PRECIPITATION ANOMALIES, NDVI AND ESPI

Dissertation presented to the Post-Graduate Program in Geodetic Sciences and Technologies of Geoinformation, Federal University of Pernambuco, as part of the requirements for obtaining a Master's degree in Geodetic Sciences and Geoinformation Technologies.

Area of concentration: Geodetic Sciences and Geoinformation Technologies.

Advisor: Prof. Dr. Rodrigo Mikosz Gonçalves.

Co-Advisor: Prof. Dr. Joseph Awange.

Recife

2019

Catalogação na fonte
Bibliotecário: Josias Machado da Silva Jr./ CRB4-1690 UFPE (BCTG)

A663d Araújo, Inessa Racine Gomes de.
Detection of agricultural drought impacts on soybeans production in Brazil (1983-2016) using precipitation anomalies, NDVI and ESPI / Inessa Racine Gomes de Araújo. – Recife, 2019.
82f., il., figs., tabs., Abrev. e sigl.

Orientador: Prof. Dr. Rodrigo Mikosz Gonçalves.
Coorientador: Prof. Dr. Joseph Awange.
Dissertação (Mestrado) – Universidade Federal de Pernambuco. CTG.
Departamento de Engenharia Cartográfica. Programa de Pós-Graduação em Ciências Geodésicas e Tecnologias da Geoinformação, 2019.
Inclui Referências e apêndices.

1. Ciências geodésicas e tecnologias da geoinformação. 2. Anomalias de precipitação. 3. NDVI. 4. Seca. 5. Soja. I. Gonçalves, Rodrigo Mikosz (orientador). II. Awange, Joseph (coorientador). III. Título.

UFPE

526.1CDD (22.ed) BCTG-2019/ 445

INESSA RACINE GOMES DE ARAUJO

DETECTION OF AGRICULTURAL DROUGHT IMPACTS ON SOYBEANS PRODUCTION IN BRAZIL (1983-2016) USING PRECIPITATION ANOMALIES, NDVI AND ESPI

Dissertation presented to the Post-Graduate Program in Geodetic Sciences and Technologies of Geoinformation, Federal University of Pernambuco, as part of the requirements for obtaining a Master's degree in Geodetic Sciences and Geoinformation Technologies.

Approved in: 02/09/2019.

EXAMINING COMMITTEE

____
Prof. Dr. Rodrigo Mikosz Gonçalves (Advisor)
Universidade Federal de Pernambuco

____
Prof. Drª. Andrea de Seixas (Internal Examiner)
Universidade Federal de Pernambuco

____
Prof. Dr. Márcio Augusto Reolon Schimidt (External Examiner)
Universidade Federal de Uberlândia

“I dedicate this work to my father (*in memorian*), with all my love and gratitude.”

ACKNOWLEDGMENT

To my family (Marlete Araújo and Milla Araújo), especially for my husband (Gildo Amancio), they always helped and encouraged me during the realization of this dream;

To Profº. Dr. Rodrigo Mikosz Gonçalves and Profº. Dr. Joseph Awange, for guidance, encouragement and kindness in sharing their knowledge.

To the Post-Graduate Program in Geodetic Sciences and Technologies of Geoinformation of the Federal University of Pernambuco, for quality teaching and dedicated teachers.

To Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES), that helped through the scholarship I complete the master's degree.

This study was financed in part by the (CAPES).

ABSTRACT

Droughts are one of the most common natural hazards in the world that can affect social and economic aspects. The objectives of this dissertation is: (i) to characterize agricultural drought on Brazilian soybeans producing areas in terms of frequency and severity, during 1983-2016 period, through precipitation anomalies and ENSO Precipitation Index (ESPI) event; (ii) establish the degree of significance between Normalized Difference Vegetation Index (NDVI) and precipitation and (iii) assess the impacts on production drought months with critical soybean yield periods. The data used are NDVI, using the AVHRR and MODIS sensors, monthly precipitation data from the soybean producing states, soybean production data and ESPI events. The methods consist of using the percentiles in conjunction with the time series analysis, the lower threshold percentile of 25% was calculated and 75% represented the highest threshold. The thresholds values are plotted in the time series, identifying extreme dryness and wetness as the two categories. The results of the anomalies pointed out the pluviometric variability throughout Brazil, registering events considered extremely dryness, during consecutive years (1985, 1989, 1990, 1991, 1994, 1995, 1999, 2001, 2002, 2005, 2007, 2011, 2012 and 2015). It is possible to observe that precipitation anomalies followed moderately to soybean production. Then, the precipitation anomalies are correlated with NDVI to demonstrate the efficiency of the index for each soybean production state. The year 2012 recorded the lowest NDVI value, reaching 0.53 and the precipitation anomaly was -0.91, in which it can be observed that the NDVI values are correlated with precipitation. It is compared the years of negative precipitation anomalies under the ESPI phenomenon, it is possible to observe that whenever ESPI obtains negative values it generates significant changes in precipitation patterns. Thus, this research is important for Brazil, as it provides alternatives to monitor and evaluate the impacts of agricultural drought on soybean production.

Keywords: Anomalies rainfall. NDVI. Drought. Soybean.

RESUMO

As secas são um dos riscos naturais mais comuns no mundo que podem afetar aspectos sociais e econômicos. Os objetivos desta dissertação são (i) caracterizar a seca agrícola nas áreas produtoras de soja do Brasil em termos de frequência e gravidade, durante o período 1983-2016, através de anomalias de precipitação e Índice de Precipitação (ESPI) (ii) estabelecer o grau de significância entre o Índice de Vegetação por Diferença Normalizada (NDVI) e as anomalias de precipitação (iii) avaliar os impactos na produção dos meses de seca com os períodos críticos de produtividade da soja. Os dados utilizados são o NDVI, utilizando os sensores AVHRR e MODIS, os dados mensais de precipitação dos estados produtores de soja, os dados de produção de soja e dos eventos do ESPI. Os métodos consistem em utilizar os percentis em conjunto com a análise de séries temporais, foi calculado o percentil do limiar inferior de 25% e 75% representou o limiar superior. O valor limite foi então plotado na série temporal, identificando seca extrema e umidade como as duas categorias. Os resultados das anomalias apontam para a existência de grande variabilidade pluviométrica em todo o Brasil, registrando eventos considerados extremamente secos, durante anos consecutivos (1985, 1989, 1990, 1991, 1994, 1995, 1999, 2001, 2002, 2005, 2007, 2011, 2012 e 2015), foi possível observar que as anomalias de precipitação responderam moderadamente à produção de soja. Em seguida as anomalias de precipitação foram correlacionadas com NDVI para demonstrar a eficiência do índice, os valores analisados correspondem à localização da produção de soja para cada Estado. O ano de 2012 registrou o menor valor de NDVI, chegando a 0,53 e a anomalia de precipitação foi de -0,91, no qual pode-se observar que os valores de NDVI responderam bem à precipitação. Foram comparados os anos de anomalias de precipitação negativas sob a influência do fenômeno ESPI, sendo possível observar que sempre que o ESPI obtém valores negativos gera mudanças significativas nos padrões de precipitação. Assim, esta pesquisa é importante para o Brasil, pois fornecem alternativas para monitorar e avaliar os impactos da seca agrícola na produção de soja.
Palavras-chave: Anomalias de Precipitação. NDVI. Seca. Soja.

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

AVHRR	ADVANCED VERY HIGH RESOLUTION RADIOMETER
DERAL	DERAL DEPARTMENT OF RURAL ECONOMY
ESPI	ENSO PRECIPITATION INDEX
GPCP	GLOBAL PRECIPITATION CLIMATOLOGY PROJECT
GRACE	GRAVITY RECOVERY AND CLIMATE EXPERIMENT
HDF	HIERARCHICAL DATA FORMAT
LAI	LEAF AREA INDEX
MODIS	MODERATE-RESOLUTION IMAGING SPECTRORADIOMETER
MRT	MODIS REPROJECTION TOOL
NETCDF	NETWORK COMMON DATA FORM
NDWI	NDWI NORMALIZED DIFFERENCE WATER INDEX
NDVI	NORMALIZED DIFFERENCE VEGETATION INDEX
NASA	NATIONAL AERONAUTICS AND SPACE ADMINISTRATION
NOAA	NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION
QGIS	QUANTUM GIS

SPI	SPI STANDARDIZED PRECIPITATION INDEX
TRMM	TROPICAL RAINFALL MEASURING MISSION

CONTENTS

1 INTRODUCTION

Soybeans crop is among the most produced grains in the world, Brazil being the second largest producer (29,9%), behind only the United States (33,9%), see e.g., (CONAB, 2015). In 2015, Brazil exported approximately 57 million tons of soybeans (AN & OUYANG, 2016), primarily to China (LIMA et al., 2017). Cultivated especially in the Central-West and South regions of the country, soybeans became one of the most outstanding products of Brazilian agriculture and trade balance (BRAZIL, 2015). Among the states of the country, the largest producer is Mato Grosso, followed by Paraná (EMBRAPA, 2015). Analysis by the United Nations Food and Agriculture Organization has indicated that soybean production in Brazil will increase by 37% over the next years (FAO, 2015). According to Golldack, Luking and Yang (2011) drought has a crucial impact on plant growth and development, thereby compromising food production for the population. Smiderle (2009) described the healthy production development of the crop, through each region, droughts occur often, generating great impacts on water resources, agriculture, and the economy. Even humid regions, like the Amazon Rain Forest in the Amazonas state and the Pampas region in the Rio Grande do Sul state, have experienced severe drought during the few last years, causing disasters for several human activities, mainly related to agriculture (BERLATO & CORDEIRO, 2005; PHILLIPS, ARAGÃO & LEWIS 2009).

In recent years, the production of soybeans has been threatened by frequent episodes of droughts with the damage representing up to 40% of the loss of the harvest (see, e.g., FARIAS, NEUMAIER & NEPOMUCENO, 2009; CONAB, 2012; MORANDO et al., 2014; MARIANO, 2015). In general, droughts have intensified in Brazil in recent times, as reported, e.g., de Nys, Engle and Magalhães (2016), Awange, Mpelasoka and Goncalves (2016), Mpelasoka, Awange and Goncalves (2017), Nóia Junior and Sentelhas (2019) and da Silva Junior (2019). However, in the studies of Panu and Sharma (2002), agricultural drought can be defined by soil water availability for crop development and is directly related to the combination of meteorological droughts and hydrological. It is one of the weather phenomena that cause most damage in agriculture and can be diagnosed through quantification indexes and statistical analyzes, as observed by Fernandes et al. (2009). According to Mishra and Singh (2010), it is now accepted that droughts in future pose a threat to climate sensitive economic sectors, specifically agriculture, and have therefore necessitated the assessment of their potential impacts on crop production at various scales. Particularly for Brazil, droughts have caused damage to its agricultural sector, e.g., prices oscillation, overload of products and companies (MARIANO, 2015). According to CEPED (2013), the number of drought occurrences in Brazil has been increasing. From 1991 to 2012, for example, it was found that 30% of the recorded drought events occurred in the first eleven years and in the second eleven-year period, 70% of drought occurrences were recorded. Due to Brazil's size, which requires volume of drought information, spatial gathering of such volume of data in a timely manner for decision-making is a daunting task to be undertaken in the field, since there are limitations of human, instrumental and financial capital. Such occurrences and impacts, therefore, shows the need for monitor systems to quantify droughts with accurate and specialized information.

Drought is one of the main factors responsible for soybean crop yield variability. In agricultural dryness reported prepared by the Ministry of Planning, Gopfert, Rossetti and Souza (1993), showed that droughts are the main ominous event (71% of cases), followed by excessive rain (22% of cases), hail and frost. Soybeans have two well-defined critical periods with respect to water scarcity: from sowing to emergence and grain filling. During germination, both excess and lack of water are harmful to crop establishment. The occurrence of water deficit during the grain-filling period is more harmful than during flowering (DOSS et al., 1974; SIONIT & KRAMER, 1977).

Currently, the development of methodologies using indices for droughts monitoring in Brazil has attracted much research interest. Mariano et al. (2018) studied drought in northeastern Brazil, detecting trends in biomass (LAI) anomalies as indicators of land degradation, trend analysis was performed for the periods ranging from 2002-2012 (no severe droughts) to 2002-2016 (including the last drought).

The drought that hits the north of Minas Gerais was the trigger of severe socio-environmental impacts, Moreira (2016) used the spatial-temporal distribution of drought to analyze between 2003 to 2014, the correlation of precipitation anomaly index and Normalized Difference Water Index (NDWI). Liu and Negron Juarez (2015) used the El Niño Southern Oscillation (ENSO) and NDVI index to construct a prediction drought model for the Brazilian Northeast using the multiple regression technique, between 1951 to 1998. The authors concluded that the use of satellite-recorded NDVI improved the correlation with ENSO indices.

Teodoro et al. (2015) analyzed the occurrence of wet and drought periods through the SPI using Standardized Precipitation Index (SPI) in Mato Grosso do Sul, the rainfall data of 29 stations collected from 1983 to 2013. Gois et al. (2013) used precipitation data from Tocantins state regions combined with Standardized Precipitation Index (SPI) for spatio-temporal analysis of drought severity on annual scale using the time series from 1976 to 2012. Spline method was used to interpolate SPI index, and finally were compared with severe drought events during strong El Niño events (1982/83, 1990/93 and 1997/98). While Blain (2012) described monthly SPI series obtained from four São Paulo state weather stations. The analyses were carried out by evaluating the normality assumption of the SPI distributions, the spectral features of these series and the presence of climatic trends in these datasets. Li et al. (2008) observed that the Standard Precipitation Index (SPI) over the southern Amazon region decreased in the period of 1970 to 1999 by 0.32 per decade, indicating an increase in drought conditions. With the development of satellite remote sensing technology, several studies have applied remote sensing data to monitor large-scale drought (KOGAN, 1995; MCVICAR & JUPP, 2002; HAO et al., 2017).

Satellite remote sensing provides a synoptic view of the land and a spatial context for measuring the impacts of drought. This technique has also been proven a valuable source of timely, spatially continuous data that can facilitate the vegetation dynamics monitoring of over large areas. Usually, the drought phenomenon is identified through indices or products that allow integrating the data to characterize the phenomenon, one the most used remote sensing systems for drought studies are the NOAA/AVHRR, the MODIS sensor aboard Terra satellite, also used in this study. Vegetation indices are spectral transformations of two or more bands that aim to enhance the vegetation properties and as a basis for the spectral signature of the green vegetation in the red and near infrared portion of the electromagnetic spectrum. For instance, the normalized difference vegetation index (NDVI) calculated from remote sensing images has been widely used to monitor drought (HENRICKSEN & DURKIN, 1986; PETERS ET AL., 2002; KLISCH & ATZBERGER, 2016), because the value of this index can be used to separate vegetation from its soil background as well as provide valuable information related to vegetation health (PETTORELLI et al., 2005).

This study, therefore, aims to contribute towards the knowledge of agricultural drought. The precipitation anomalies are analyzed and correlated with vegetation index using the AVHRR and MODIS remote sensor (years of drought) to observe the impacts of land cover. Thus, it is possible to detect extreme periods of agricultural drought, the relationship with the agricultural production, and establish the significance between NDVI, precipitation and ESPI events according to the following objectives.

1.1 OBJECTIVES

1.1.1 General objective

The general objective of this research is to analyze the impacts of agricultural drought on soybeans production in Brazil between 1983 and 2016 (33 years).

1.1.2 Specific objectives

- The characterization of agricultural drought on soybeans producing areas of Brazil in terms of frequency and severity, during 1983-2016 period, through precipitation anomalies and ESPI event;
- Establish the degree of significance between NDVI and precipitation anomalies;
- The drought month’s impact assessment of the critical soybean yield periods.

1.2 OUTLINE OF THE THESIS

This dissertation is structured as follows: chapter 2 describes the events of ESPI and their importance to Brazil. It shows how drought types are classified and the importance of agricultural drought and its impact on soybean production. It also describes the sensors used to generate NDVI and in turn characterize agricultural drought. Chapter 3 presents the study area, describes the applied methodology and the data that were used to obtain precipitation anomalies and NDVI, ESPI and soybean production. In Chapter 4 are the results, including drought years, the correlation between years of production and their analysis. It established a correlation between precipitation anomalies and NDVI, along with ESPI events. And finally, to assess the impacts drought months with critical soybean yield periods. Chapter 5 finalize with conclusions and recommendations.

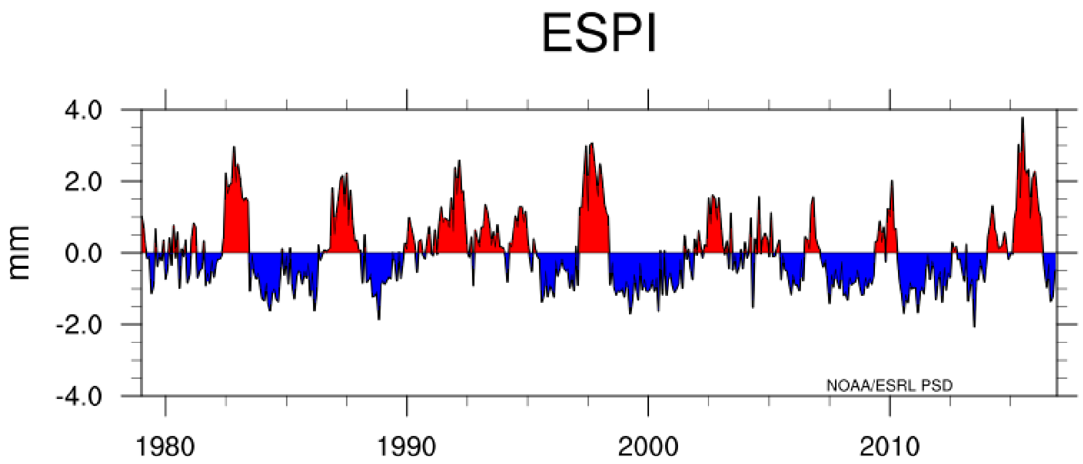
2 THEORETICAL FOUNDATION

This chapter is divided into three items: 2.1 shows the ENSO Precipitation Index (ESPI) background which is an index for the El Niño-Southern Oscillation (ENSO) based on precipitation from Global Precipitation Climatology Project (GPCP); 2.2 present the theoretical background of the agricultural drought, in which are obtained the anomalies precipitation indexes and 2.3 the baseline of NDVI.

2.1 Precipitation Index - ESPI

Curtis and Adler (2000) introduced an index for the El Niño-Southern Oscillation (ENSO) based on precipitation from Global Precipitation Climatology Project (GPCP) called the Precipitation Index (ESPI). The El Niño Index (EI) and La Niña Index (LI) are in turn combined to create the ESPI index. Figure 1 shows the ESPI time series in a graphic, in which values that are in the negative phase are related to La Niña events, that in turn the rains are below normal, while the values that are in the positive phase are related to El Niño events, that in turn the rains are considered above normal. The latest value ESPI was in November 2016 (-0.47).

Figure 1 - Time Series of ESPI (1979-2016).



Source: Adapted from NOAA/ESRL (2018).

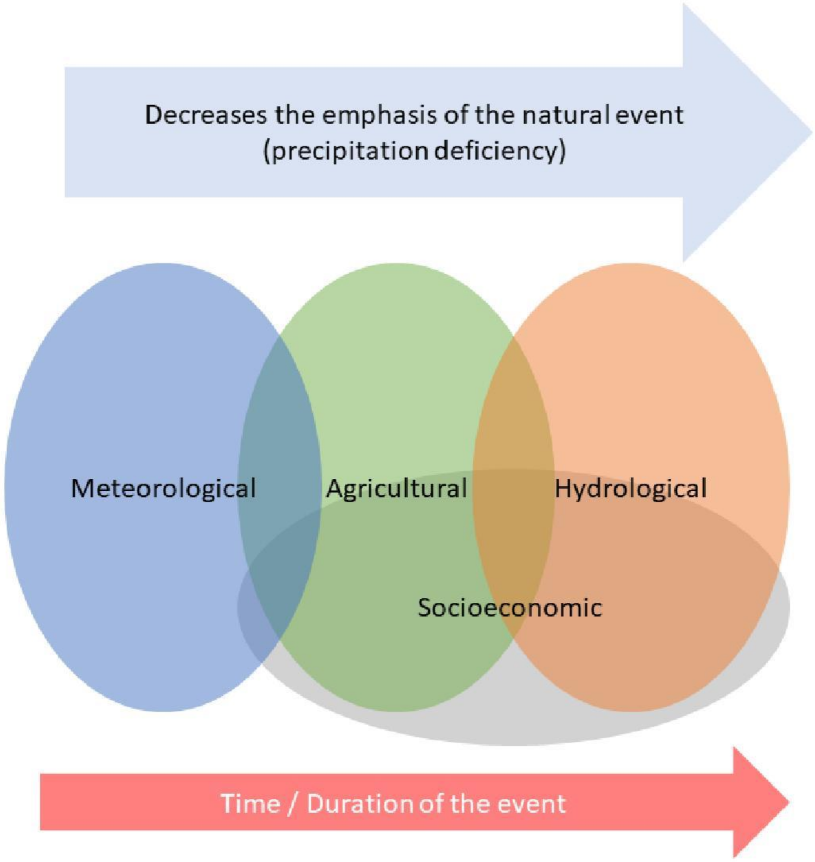
An important source of climate variability in Brazil is the El Niño Southern Oscillation (ENSO) phenomenon (STUCK et al., 2006). The positive ENSO phase, known as El Niño, is normally related to droughts in the northern part of the country, including Northeast Brazil and the Amazon Rain Forest. On the other hand, the negative phase (La Niña) normally intensifies the drought spells in southern Brazil, including the states of Paraná, Santa Catarina, and Rio Grande do Sul, both are correlated with drought events in the results session.

2.2 AGRICULTURAL DROUGHT

Droughts are one of the most common natural hazards worldwide that impact social and economic aspects. It is commonly classified as **meteorological droughts** when the precipitation levels are lower than the annual averages; **hydrological droughts** are generally associated with a river basin or river, defined as negative effects on the flow of a river, reservoir level, subsurface water supply among other bodies of water; already the **agricultural drought**, which is the object of this study, is the negative impact on the availability of water in the soil with respect to plants supply, compromising its productivity or condition; it is usually caused by the precipitation deficit, but may also be due to inadequate management of water and soil resources (WARDLOW et al., 2012). Although some authors consider one more type, the **socioeconomic drought** (BOKEN et al., 2005; NDMC, 2006; WILHITE AND GLANTZ, 1985), which refers to the situation that occurs when water scarcity affects people and is associated with supply and demand for goods and services.

The effects of drought take two or three months to appear and once the event has started, can last for months or years. The magnitude of the effects is closely related to the timing of the lack of precipitation and the intensity and duration of the event. The meteorological drought is distinguished mainly by its natural characteristic, and the agricultural, hydrological and socioeconomic, by the demands of society and the environment. According Sausen and Lacruz (2015) the first sector to be harmed when the drought happens is agricultural, due to its strong dependence on water stored in the soil. If deficiencies in precipitation continue, people who depend on other sources of water will begin to experience the effects of scarcity (Fig. 2).

Figure 2 - Relationship between meteorological, agricultural, hydrological and socioeconomic drought.

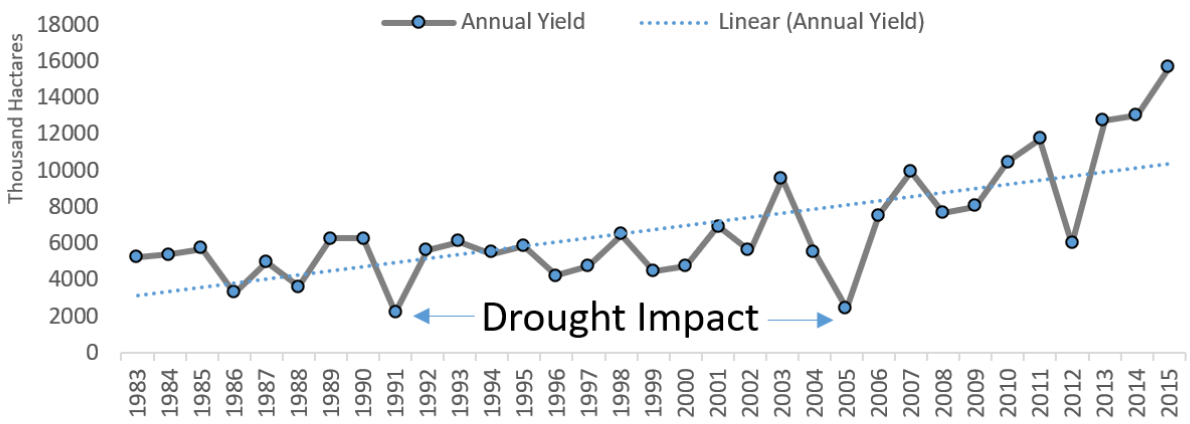


Source: Adapted from NDMC (2006).

According to Boken (2005) agricultural drought can cause serious disasters for food security, since crop yields are directly affected by soil moisture shortage. Drought assessment, monitoring, and preparedness planning should be considered essential components of integrated water resources management systems, as mentioned by Wilhite (2005), to reduce societal vulnerability to future drought events. The drought impacts in Brazil are diverse, depending on the duration and intensity of the dry period, the region, and the season.

Some of these adverse drought impacts include yield losses in agriculture, which is one of the main economic activities in the country. Agricultural drought can be detected when continuous and intense soil moisture stress leads to significant yield reduction, as shown in Fig. 3.

Figure 3 - Historical soybean yield data for Rio Grande do Sul state, Brazil, showing intense droughts impacts on yield losses.



Source: the author (2019).

Agricultural drought is a situation when rainfall is inadequate during the crop season to support the timely cultural practices and healthy crop growth (SAI et al., 2016). For agricultural drought monitoring, precipitation anomalies are used, which in turn are correlated with the soybean production and vegetation index.

2.3 NDVI

The NDVI is a numerical indicator that uses red and near-infrared bands of the electromagnetic spectrum, and is used to analyze remote sensing measurements and assess whether the target being observed contains live green vegetation. NDVI has found a wide application in vegetative studies, as it has been used to estimate crop yields and performance. It is often directly related to other ground parameters such as percent of ground cover, photosynthetic activity, surface water, leaf area index, and amount of biomass. Because of this, the severity of a drought situation can be assessed by the extent of NDVI deviation from its long-term mean (see, https://www.academia.edu/9563468/NDVI).

The NDVI (ROUSE *et al*., 1974) is certainly the most used vegetation index to characterize the drought, which is evidenced by the numerous applications, being one of them present in this work: the detection of agricultural drought. The time series of Vegetation Index (NDVI), generated with NOAA satellite data, has been used to identify and classify terrestrial vegetation, estimate primary vegetation production, monitoring drought, characterize vegetation dynamics, estimate precipitation, estimation of carbon dioxide concentration, and surface temperature estimation (BARBOSA, 1998).

2.3.1 ADVANCED VERY HIGH RESOLUTION RADIOMETER (AVHRR)

In 1982 the Global Inventory and Monitoring Modeling Group (GIMMS) of the National Aeronautics and Space Administration (NASA) dedicated to multitemporal vegetation studies using AVHRR / NOAA data. The main objective of the group was to evaluate the use of satellite data of low spatial resolution to provide information on the distribution and phenology of vegetation. Table 1 describes the main characteristics of the AVHRR sensor system and the orbital parameters of the NOAA satellites, downloaded from (http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/).

Table 1: Orbital and imaging characteristics of the AVHRR / NOAA sensor system.

Cycle of Coverage	9 days
Scanning Angle	55,4°
Image Range	2.400km
Altitude Orbital	833km
Orbital Inclination	98,8km
Orbital Period	102min
Number orbit/day	14,1
InstaForex Field of View (IFOV)	1,4mrad
Nadir Resolution	1,1km
Quantization	10bits

Source: Adapted from Kidwell (1991).

Although the AVHRR sensor spectral channels have been chosen to provide meteorological, oceanographic and hydrological parameters, the system has characteristics that make it possible to study vegetation monitoring. Channel 1 of the AVHRR sensor (0.58-0.68mm) is the part of the spectrum where chlorophyll causes considerable absorption and channel 2 (0.725-1.1mm) is the part of the spectrum where the spongy structure of the leaf (mesophyll spongy) causes high reflectance. Many combinations of channels 1 and 2 have been proposed to obtain the maximum contrast of these properties for better characterize the vigor of the vegetation. Many vegetation indices have been proposed based on the premise of spectral contrast of reflectance between vegetation and background elements in the scene (Rouse *et al.,* 1974). Table 2 describes the spectral range of each AVHRR / NOAA sensor channel and its applications.

Table 2: AVHRR / NOAA spectral channels and radiometer applications.

CHANNEL	**TIROS N (μm)**	**NOAA 6,8 e 10 (μm)**	**NOAA 7, 9, 11, 12, 14 (μm)**	**APPLICATION**
1	0.55 - 0.90	0.58 – 0.68	0.58 – 0.68	Mapping of clouds, ice and snow.
2	0.725 – 1.10	0.725 – 1.10	0.725 – 1.10	Mapping of water bodies, vegetation monitoring (combined with channel 1)
3	3.55 – 3.93	3.55 – 3.93	3.55 – 3.93	Nocturnal cloud mapping, TSM; detection of fires and volcanic activities.
4	10.5 – 11.5	10.5 – 11.5	10.3 – 11.3	Daytime and nighttime mapping of clouds, TSM, soil moisture, volcanic activities
5	REPEAT CANAL 4	REPEAT CANAL 4	11.5 – 12.5	Daytime and nighttime mapping of clouds, TSM and soil moisture.

Source: Adapted from USGS, 2019.

2.3.2 MODIS Vegetation Index (NDVI and EVI)

MODIS vegetation index produced on 16-day intervals, at multiple spatial resolutions, provide consistent spatial and temporal comparisons of vegetation canopy greenness, a composite property of leaf area, chlorophyll, and canopy structure. Two vegetation indices are derived from atmospherically-corrected reflectance in the red, near-infrared, and blue wavebands; the normalized difference vegetation index (NDVI), which provides continuity with NOAA's AVHRR NDVI time series record for historical and climate applications, and the enhanced vegetation index (EVI), which minimizes canopy-soil variations and improves sensitivity over dense vegetation conditions. The two products more effectively characterize the global range of vegetation states and processes (see, https://modis.gsfc.nasa.gov/data/dataprod/mod13.php).

The index used in the study is the NDVI, using the MOD13A2 version. The MOD13A2 product provides Vegetation Index (VI) values at a per pixel basis at 1 kilometer (km) spatial resolution. There are two primary vegetation layers. The first is the Normalized Difference Vegetation Index (NDVI), which is the continuity index by the existing National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) derived NDVI. The second vegetation layer is the Enhanced Vegetation Index (EVI), which has improved sensitivity over high biomass regions. The algorithm for this product chooses the best available pixel value from all the acquisitions from the 16-day period. The criteria used is low clouds, low view angle and the highest NDVI/EVI value (USGS, 2019).

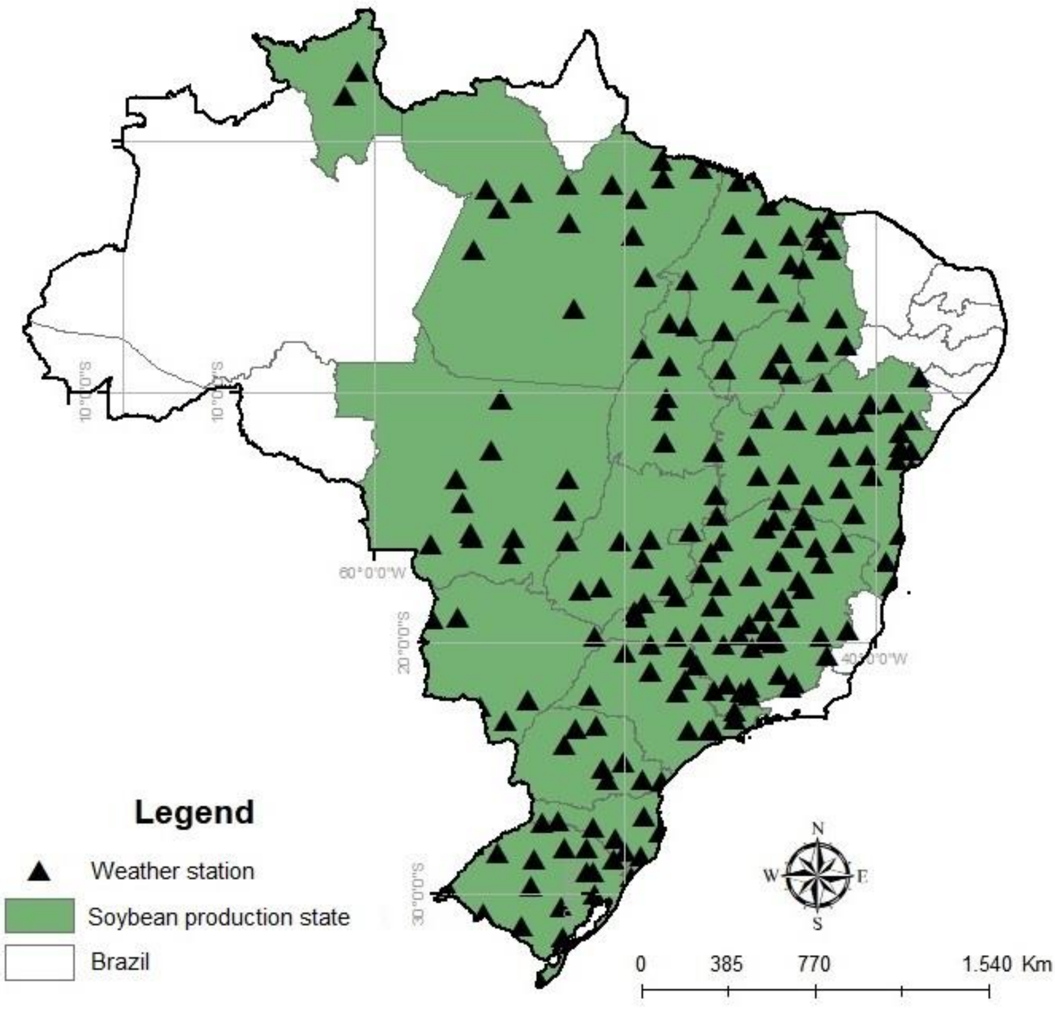
3 MATERIALS AND METHODS

This chapter presents the study area (3.1) describing the soybean producing states in Brazil; the rainfall and NDVI data (3.2) and in 3.3 the methods applied.

3.1 STUDY AREA

Figure 4 shows the area of study that comprises the soybean producing states in Brazil and their respective weather stations, located between latitudes 5°30'N and 34°00'S and longitudes 74º00'W and 34°00'W (Fig. 4). Brazil is the largest country in South America and has about 206,000,000 inhabitants (IBGE, 2016).

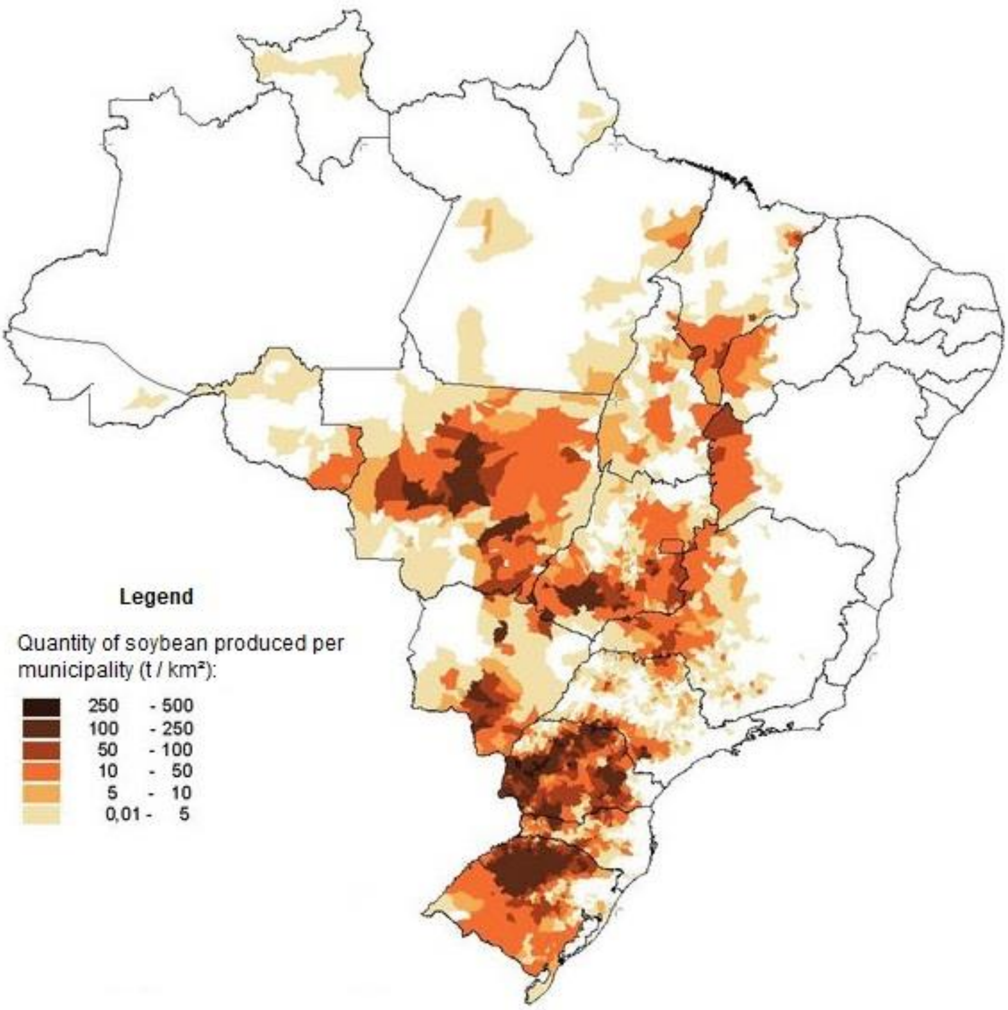
Figure 4 - Study area with soybean production states and weather stations.



Source: (modified from IBGE, 2019).

Except for a large part of São Paulo state, and the states of Amazonas and Pará, south of the parallel 6°S and between the meridians 44° and 52°W, the soybean plantations represent in area the Brazilian municipalities. In the northwest of Paraná state and northwestern Rio Grande do Sul, the plantations fill more than 50% of most municipalities area. Fig 5 shows the quantity of soybean produced per municipality in Brazil, highlighting the municipalities of the Midwest and South, where most produce soybean.

Figure 5 - Soybean production in Brazil.



Source: (modified from IBGE, 2017).

a) Study area rainfall, general characteristics

The annual rainfall above 2.500 mm is detected mainly in northern Brazil, as well as in the central coast of São Paulo state where annual rainfall achieves more than 3.000 mm on average, promoted by the orographic effect related to Serra do Mar Mountains (CONTI and FURLAN, 2011). Moreover, annual rainfall less than

700 mm occurs in Borborema Plateau, Paraiba Agreste (semi-arid region), São Francisco river Valley and northern Bahia, the driest regions of the country, also named as Backwoods. EMBRAPA (2018) reported that the temperature increase may lead to a decrease in the regions suitable for grains cultivation in Brazil. This could generate a significant change in the agricultural landscape and specifically soybeans could be the most impacted crop (the worst-case scenario would reach 40% losses by 2070).

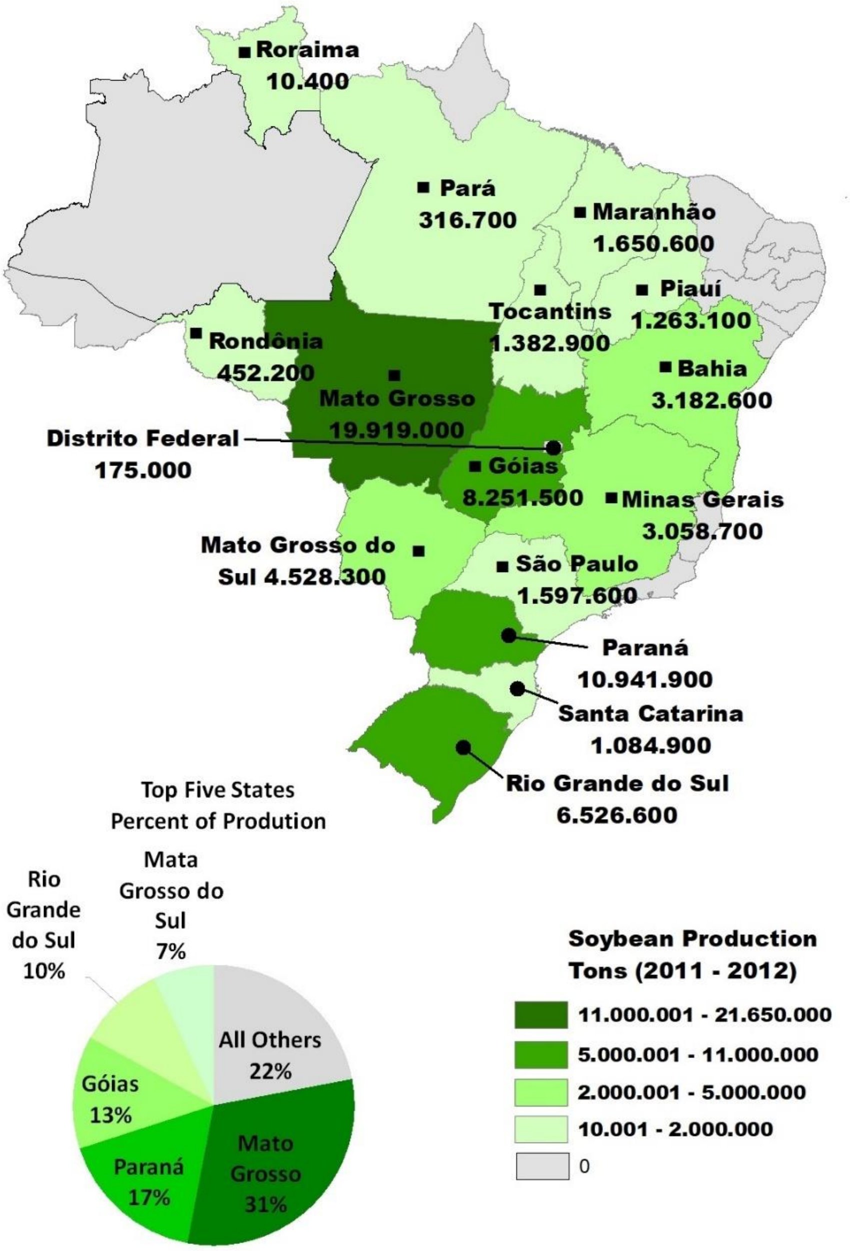
b) Soybean production

In the 1960s and 1970s, Brazil experienced industrialization and urbanization processes combined with strong economic growth, however, without the same correspondence in the agricultural sector, characterized by low productivity. A considerable part of the domestic food supply came from imports. Between 1977 and 2017, grain production, which was 47 million tons, grew more than five times, reaching 237 million tons (EMBRAPA, 2018).

Brazilian agriculture has an important role in the world scenario, in the last five decades the country has gone from importing food to one of the most important producers and exporters in the world. Brazil is the world's second largest producer of soybeans, third in corn, first in coffee, first in sugar, first in orange juice, first in ethanol and first in a number of meats and fruits (see, http://www.soybeansandcorn.com/Brazil-Land-Utilizationt). In relation to soybeans, it stands out as the most cultivated grain with about 94.2 million tons of production in 31.5 million hectares.

In the North region, the largest cultivated area is in the state of Tocantins, however, the area under cultivation in the Pará state has shown a gain in planted area, with a 9.8% increase when compared to the previous harvest (CONAB, 2015). Figure 6, shows soybean production by state considering the years 2011-2012, and it is possible to observe the behavior of soybean production by states, which Mato Grosso state leads the ranking. Brazilian production represents 25% of total world production (https://campus.hesge.ch/commoditytrading/archives/14002).

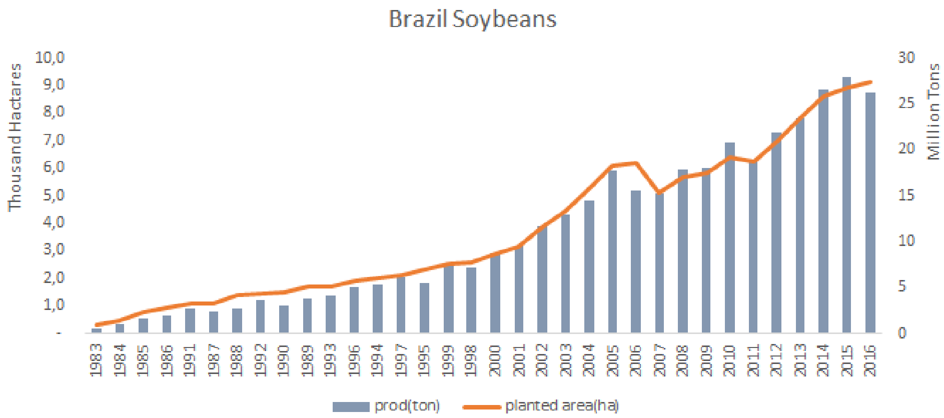
Figure 6 - Soybean production by state and your production.



Source: (CONAB–Historical Series/ USDA – FAS (2018)).

Fig. 7 shows the temporal distribution (1983 to 2016) of the planted area and the soybean production in Brazil.

Figure 7 – Evolution of: Planted area x productions of soybeans.



Source: IBGE (2019).

The drought scenario is one of the main constraints unsettling food security correlating with the survival of more than two billion people, settled around 41% of the world's area. In Brazil, the most drought-affected area is the semi-arid region (EMBRAPA, 2017). However, this could be present in whole country, according to FAO (2015) severe drought impacts in the major producing states such as Paraná, parts of São Paulo and Mato Grosso have reported maize and soybean delayed on planting operations and the reduction of planted area.

During the year 2005, around one-third of the country suffered from drought conditions, including the Amazon, the Northeast and the South (TADDEI & GAMBOGGI, 2010). According to the data on the occurrence of disasters available in the Brazilian Atlas of Natural Disasters between 1991 and 2012, 19.517 drought occurrences were recorded throughout Brazil.

According to EMBRAPA (2015), an important challenge will be the reduction of losses due to water and soil erosion, even in areas managed by the no-tillage system, considering several regions of the country. Besides the intensification of the erosive processes, it has been observed the crops productivity, due to plants susceptibility of water stresses. No-tillage, based on monoculture (soybean-fallow) and, less frequently, on simple successions of the soybean-corn type or, more rarely, on successions such as millet, soybean-wheat or soybean-out-black-, has caused continual loss of biodiversity.

3.2 DATA

The data needed to perform the analysis are:

(1) Meteorological stations of rainfall data over Brazil to generate the anomalies. The monthly rainfall data were obtained by the INMET database, through the platform (http://www.inmet.gov.br/portal/index.php?r=bdmep/bdmep);

(2) Normalized Difference Vegetation Index (NDVI) from the AVHRR and MODIS sensors. The monthly NDVI images of the NOAA/AVHRR satellites, come from the GIMMS project file, downloaded from (http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/). The images are organized in "NetCDF" (Network Common Data Form) format, in a file with 30 years of monthly NDVI for the South America surface and correspond to the drought period. Also are used the MODIS sensor (Terra satellite). This data is available considering different products, among them stand out for vegetation studies disposed on the Earth's surface, MOD09, which are surface reflectance values, MOD13, which are EVI and NDVI vegetation indices and MOD15, which are used as Leaf Area Index (LAI). For this study, the MOD13A2 are selected and downloaded from: https://search.earthdata.nasa.gov. The images are organized in "hdf" (Hierarchical Data Format) format, the treatment of MODIS data is performed in specific programs developed by NASA, free available of charge, an example is the MRT (MODIS Reprojection Tool), used in this research. The MOD13 was developed to provide consistent information on vegetation conditions from spatial and temporal comparisons, containing blue, red and near infrared bands, this data are available every 16 days (temporal resolution) with a spatial resolution of up to 1km. The total of 1064 images were used, referring to the same drought years detected, and the mosaic of these images were made to generate the NDVI, through the software QGIS.

(3) The ESPI data used downloaded from https://www.esrl.noaa.gov/psd/data /correlation/espi.data is consider as a phenomenon that extends over large spatial area and can have a different seasonal evolution from event to event. The El Niño Index (EI) and La Niña Index (LI) are in turn combined to create the ESPI index, it helps to characterize ENSO and through these indices it is possible to establish a relation with precipitation anomalies;

(4) National annual soybean production data for Brazil, downloaded from Brazilian Institute of Geography and Statistics (IBGE) by the Automatic Recovery System data portal (https://sidra.ibge.gov.br/Tabela/1612) was used to evaluate the efficiency of precipitation anomaly and vegetation index in the capture of agricultural droughts.

All the data sets are summarized in Table 3.

Table 3 - Main characteristics of datasets used in this study

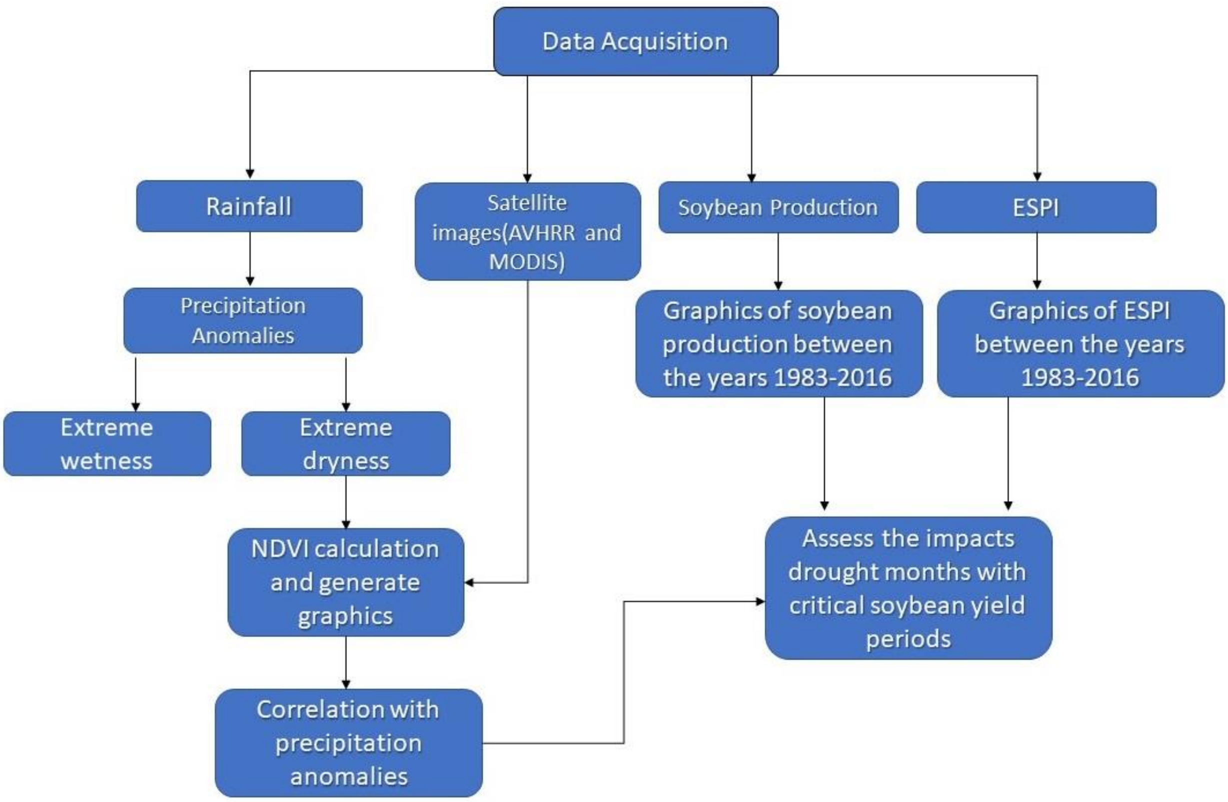
Data	Period	Spatial Resolution	Temporal Resolution
Metereological Station	1983-2016	-	Monthly
AVHRR	1983-2016	8km	15 days
MODIS	2000-2016	1km	16 days
ESPI	1983-2016	-	Monthly
Soybean Production	1983-2016	-	Annual

Source: The Author (2018).

3.3 METHODOLOGY

Figure 8 shows the methodological flowchart used in this research. The first step is related to data acquisition item 3.2: rainfall, satellite images (AVHRR and MODIS), soybean production and ESPI. With rainfall data precipitation anomalies are evaluate to characterize agricultural drought in terms of frequency and severity, according to soybean producing states in Brazil, identifying extreme dryness and wetness (next item 3.3.1 explains it in more details). Then, after identifying the years of extreme drought, the NDVI temporal series are calculated producing graphs for the AVHRR and MODIS sensors. Then the NDVI time series are correlated with precipitation anomalies to establish a statistically significant relationship between them. The soybean productivity data and ESPI are used to correlate with precipitation anomalies. The last step is to assess the impacts drought months with critical soybean yield periods through the graphs generated.

Figure 8 - Methodological flowchart used to assess the impacts of agricultural drought on soybean production.



Source: The Author (2019).

3.3.1 Precipitation anomalies

The data were organized and tabulated in order to obtain precipitation and production anomalies. The anomaly analyzes the frequency of the drought and rainy years and their intensity. To compare the data, precipitation and production data were standardized using equation 1:

$$z = \frac{x_t - \bar{x}_{33}}{\sigma} \quad (1)$$

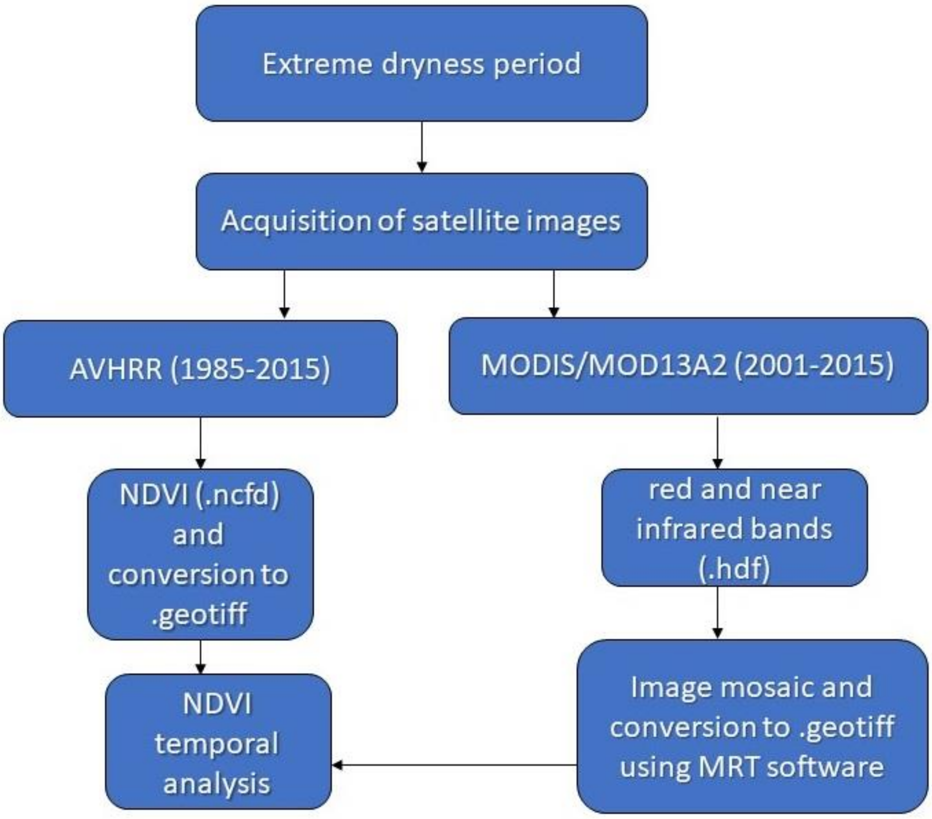
where z is the standardized value, x_t the observed value at a particular time, $\bar{x}_{33}$ the 33 years mean for the parameter and σ is the standard deviation. This gives the anomalies that were used for the time series graphics. Anomalies of the parameters were used for the comparison between rainfall and production variables from the standardized values of z in Eq. (1).

The time series and relational analysis were then performed, the data were sorted in descending order; the percentile of 25% and 75% are calculated representing the lower and higher threshold respectively, the percentages were used based on the criteria established in AWANGE (2007). The threshold values were then plotted in the time series, identifying extreme dryness and wetness as the two distinguish categories.

3.3.2 Normalized difference vegetation index (NDVI)

Figure 9 shows the methodological structure used to generate the NDVI. Considering the drought month's identification, satellite images were acquired as explained in the materials section 3.2, which in turn obtained data from the AVHRR and MODIS sensors. A correlation with the NDVI data was made to evaluate the soil over condition over these drought months.

Figure 9 - Methodological flowchart used to generate the NDVI.



Source: The Author (2019).

The NDVI approach is based on the fact that healthy vegetation has a low reflectance in the visible portion of the electromagnetic spectrum due to absorption by chlorophyll and other pigments, and high reflectance in the NIR because of the internal reflectance by the mesophyll spongy tissue of a green leaf (CAMPBELL, 1987). The NDVI is calculated by the ratio of red and the NIR bands of a sensor system according to equation 2:

The NDVI is calculated according to equation 2:

$$NDVI = \left(\frac{\mathrm{nir} - \mathrm{red}}{\mathrm{nir} + \mathrm{red}}\right) \tag{2}$$

where:

nir = near infrared band (0,75 – 0,90 μm);

red = red band (0,63 – 0,70 μm).

The NDVI is based on the spectral signature of the plants, Karaburun (2010) describes that it provides values between -1 and +1 based on the surface reflectance, the negative values of NDVI (NDVI <0) correspond to water bodies, values very low (NDVI <0.1) indicate infertile areas, already values considered moderate (0.2 <NDVI <0.3) represent areas of pasture and shrubs, (0.6 < NDVI <0.8) express tropical and temperate forests and indicate the presence of “living vegetation”, and finally the exposed soil has null value (NDVI = 0) (CHOUHAN & RAO , 2017). The NDVI allows plant cover studies to be performed more efficiently, because with multi-temporal analyzes of these data leads to the evaluation of the variation of green area in a certain period of time, therefore, the vegetation index is widely used for remote sensing applications focused on agricultural drought.

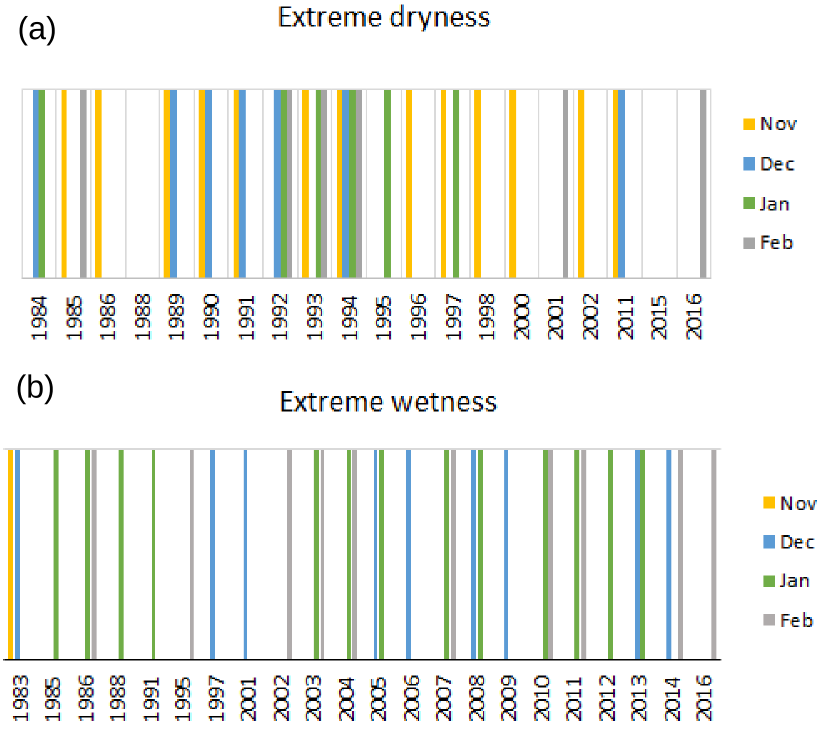
4 RESULTS AND DISCUSSIONS

This chapter shows the results and discussion including drought year's detection, the correlation between the precipitation anomalies and the NDVI. Finally, the agricultural drought impacts assessment on soybean production from precipitation anomalies, NDVI and ESPI events.

4.1 DROUGHT YEARS

The results of precipitation anomalies identify extreme dryness and wetness as the two main categories (Figure 10a, 10b), through the threshold. Drought years indicates that the period from 1985 to 1999 shows drought largely with lower negative anomalies, highlighting for the years 1992 to 1994, in which consecutive droughts occurred (see, Fig.10a). It is observed that November is the month that mostly suffers from drought and it is the exactly the soybean growth month. While the period from 2003 to 2010 was considered more rainy with positive anomalies, mainly the month of January (see, Fig.10b). The period from 2011 to 2016 shows a mixture of wet and dry years.

Figure 10 - Periods of drought and their intensity (a) extreme dryness (b) extreme wetness.



Source: The Author (2019).

The results of the anomalies point to the existence of great pluviometry variability throughout Brazil, registering events considered extreme dryness, during consecutive years (see, table 4).

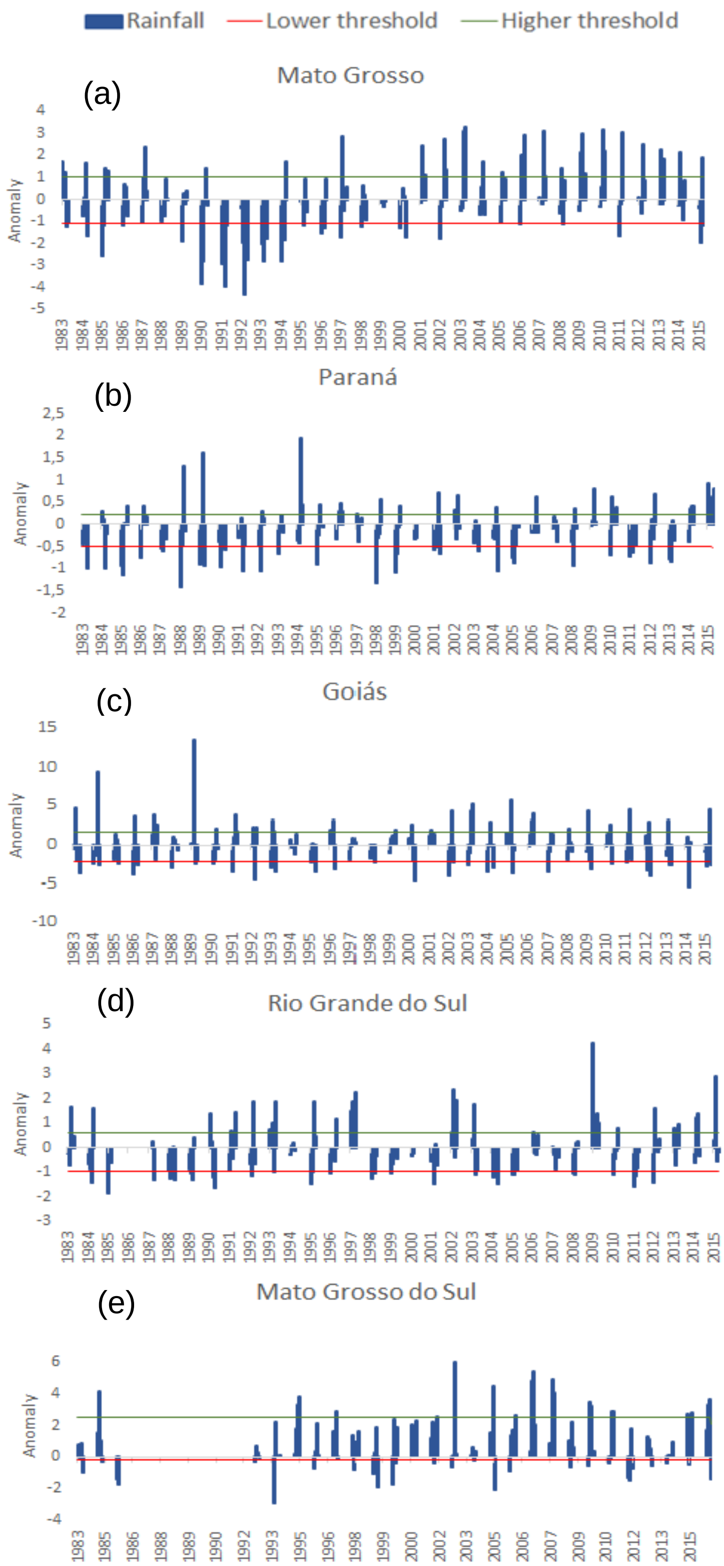
Table 4 - Periods of drought and their intensity

Drought	Year
Extreme	1985, 1989, 1990, 1991, 1994, 1995, 1999, 2001, 2002, 2005, 2007, 2011, 2012 and 2015

Source: The Author (2019).

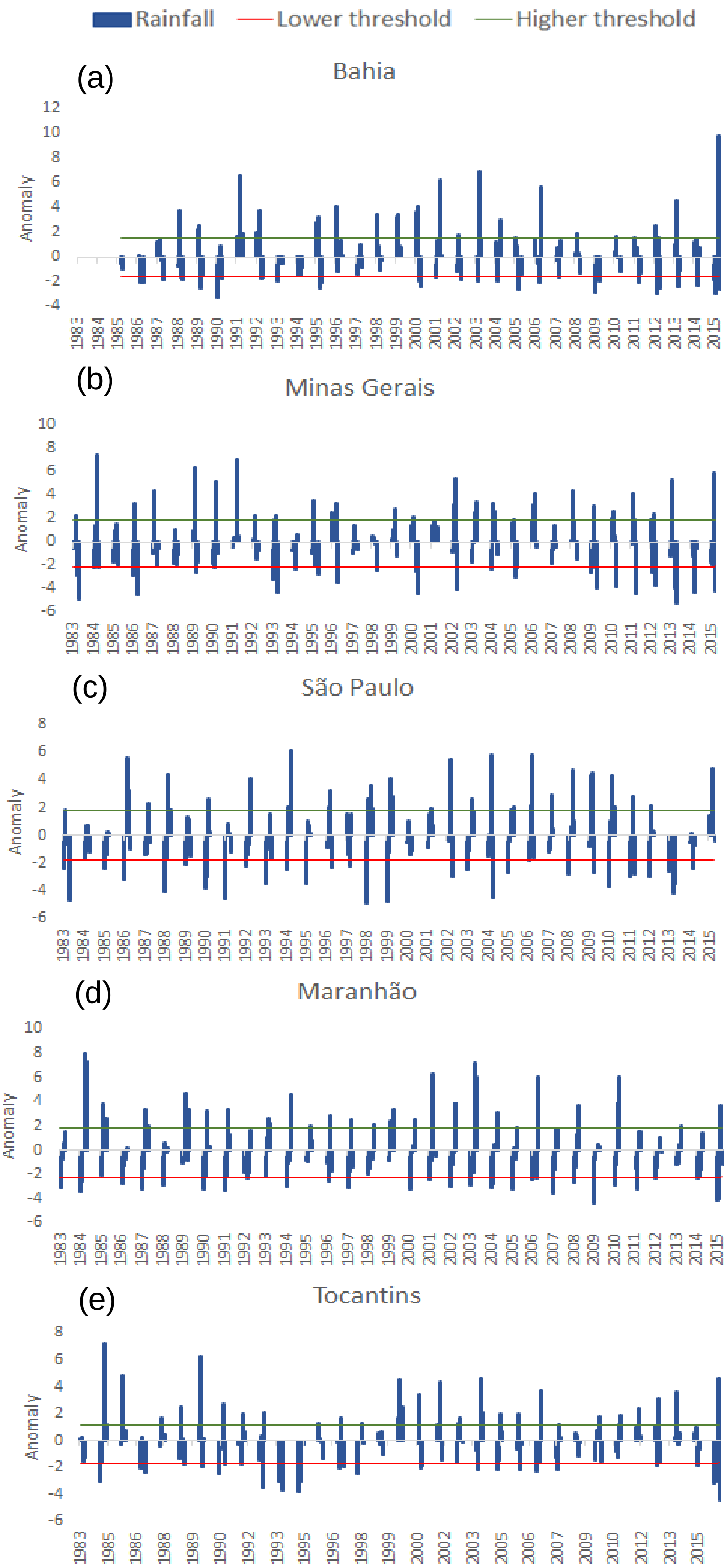
The drought years are obtained from the observation of the lower thresholds (25% of the normal and below represented the ‘lower threshold’), for the months of November to February (months of soybean growth and development) for the soybean producing states of Brazil (Fig. 11 and 12). This method was used to determine the frequency, severity and drought duration, it was found that the occurrence of positive anomalies was slightly higher than the negative, but during soybean growth, an extreme drought can be expected every 2 to 4 years.

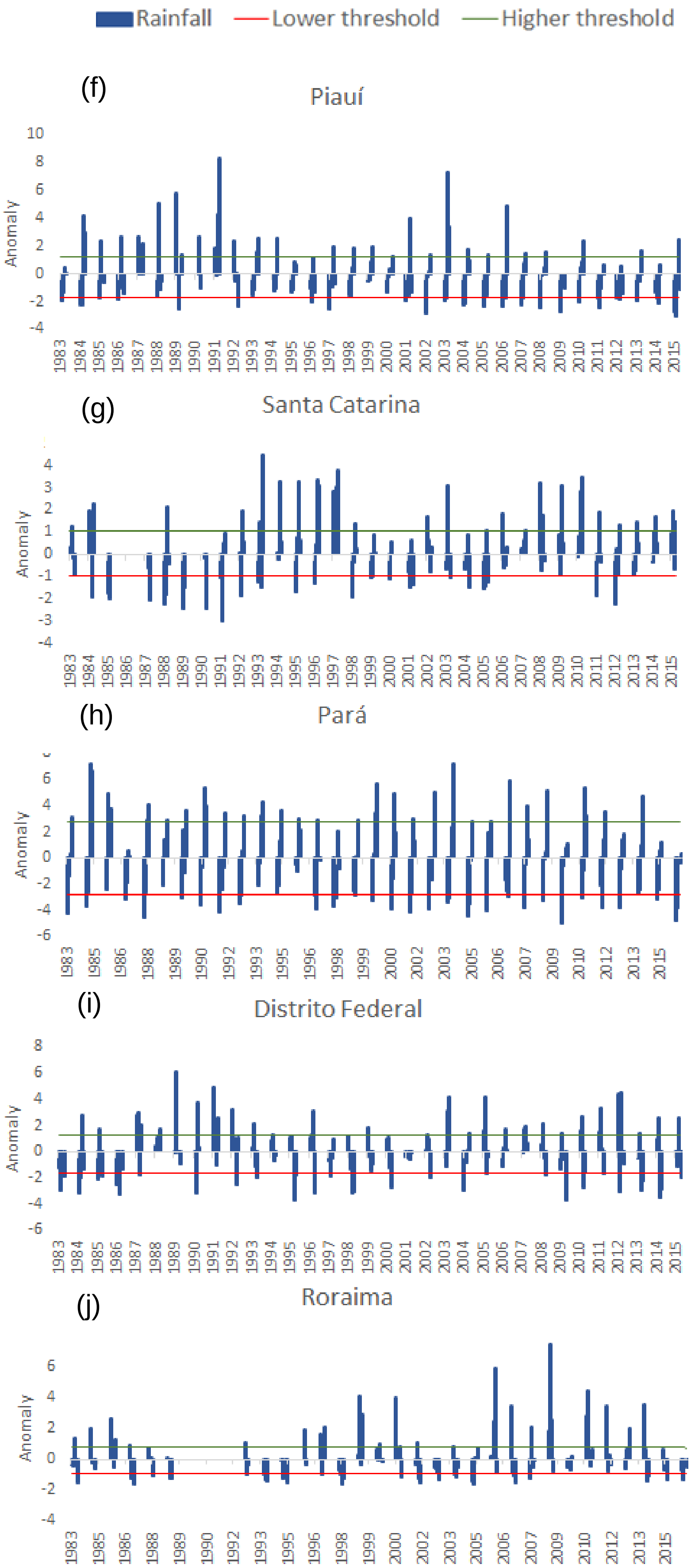
Figure 11 - Precipitation anomalies from 1983 to 2016 for the top five soybean production states (a) Mato Grosso (b) Paraná (c) Goiás (d) Rio Grande do Sul (e) Mato Grosso do Sul.



Source: The Author (2019).

Figure 12 - Precipitation anomalies from 1983 to 2016 for the other states. (a) Bahia (b) Minas Gerais (c) São Paulo (d) Maranhão (e) Tocantins (f) Piauí (g) Santa Catarina (h) Pará (i) Distrito Federal (j) Roraima.

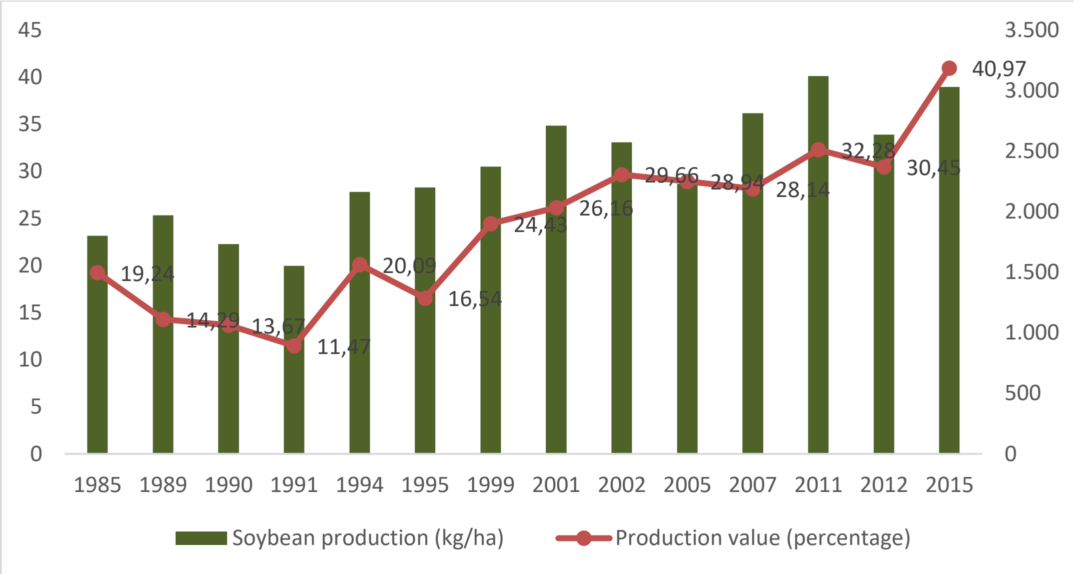




Rainfall
Lower threshold
Higher threshold
(f)
Piauí
Anomaly
(g)
Santa Catarina
Anomaly
(h)
Pará
Anomaly
(i)
Distrito Federal
Anomaly
(j)
Roraima
Anomaly

From the drought profile in Figure 13, which shows the relationship between drought years and yield and soybean value, where as in turn as production decreases the value of soybeans also, especially in the years 1991, 1995 and 2012 that there is a significant decrease.

Figure 13 - Agriculture drought profile in relation to soybean production and value.



Source: IBGE (2016).

A relationship was established between precipitation anomalies and soybean yield (Fig. 14), which indicates that as drought severity increases, yields fall, and it also shows that drought severity declines, for example in 1984, 2008 and 2015, were years of relief for soybean growers, it can be seen that were years of heavy rainfall and consequently an increase in production after years of extreme drought.

The correlation between precipitation and production values are also included in the work (see, figure 14(a2…e2), 15(a2…d2) and 16(a2…f2)). From the scatter plots it can be seen than precipitation anomalies values responded moderately to soybean production (see, table 5, about the correlation coefficient values classification).

Table 5 - Classification of correlation coefficient values

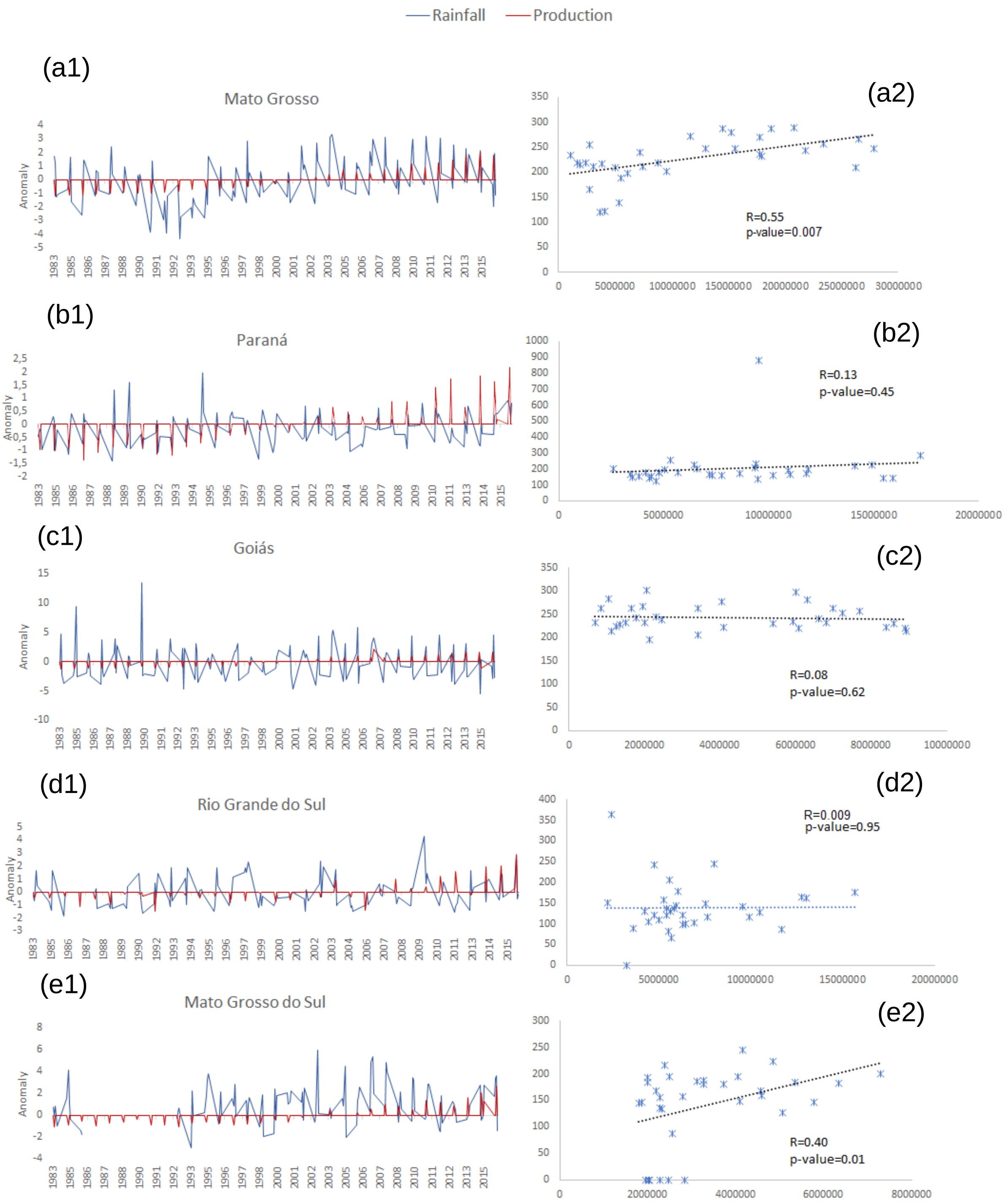
Coefficient correlation	Classification
0.0 to 0.1	very low
0.1 to 0.3	low
0.3 to 0.5	moderate

0.5 to 0.7	high
0.7 to 0.9	very high
0.9 to 1.0	almost perfect

Source: Cohen (2013).

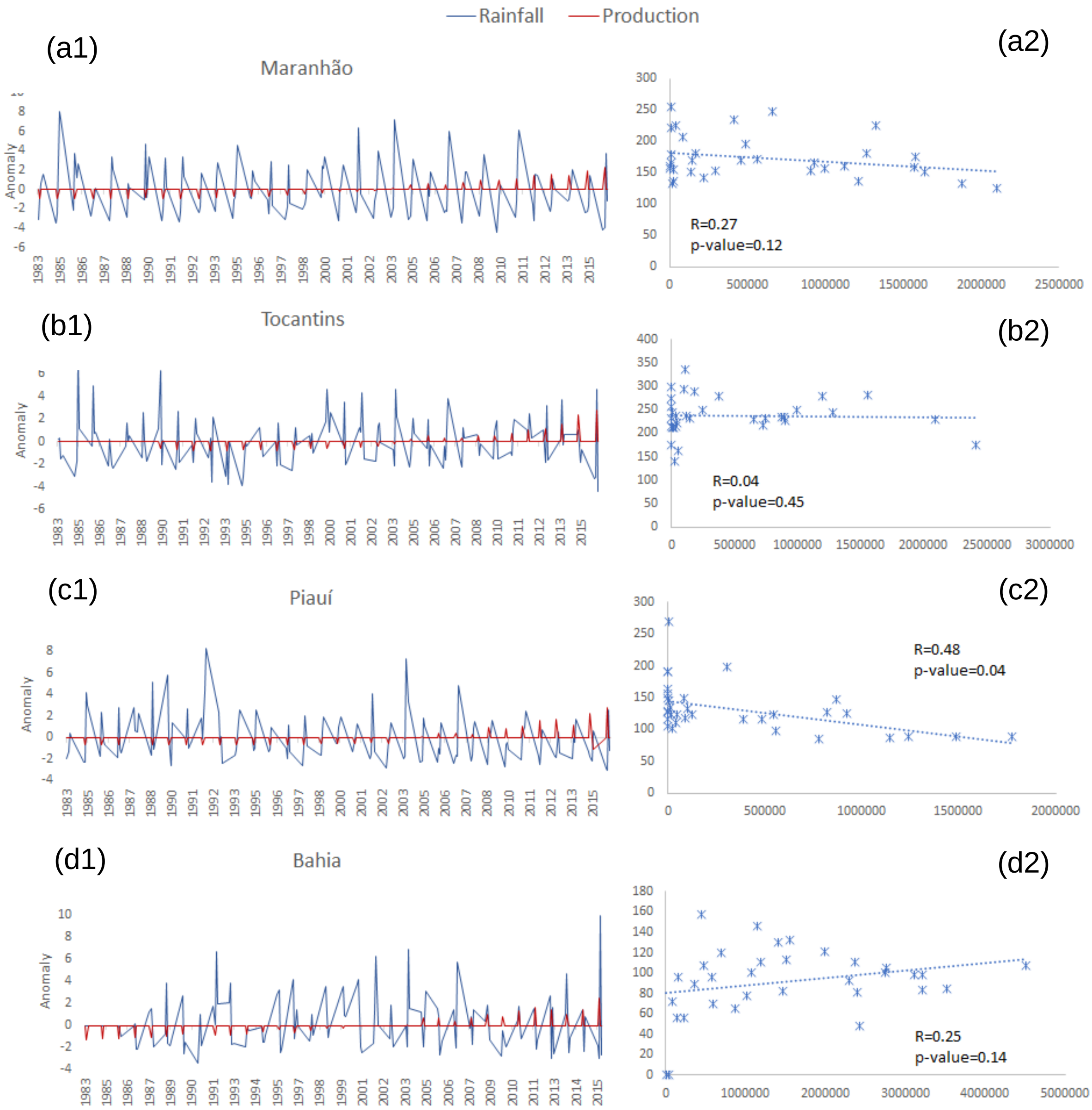
The graph shows a positive relationship between the two variables in most of the studied states, but in the states of Piauí (Fig. 15c2), Pará (Fig.16d2) and Roraima (Fig. 16f2), it is possible to see that there is a negative relationship of the variables, may be due to the lack of information on the studied years of both precipitation and grain yield. The appendix A shows the regression statistics summary results for the states.

Figure 14 - Precipitation and soybean production anomalies of the top five soybean production states from 1983 to 2016 (a1) Mato Grosso (a2) correlation of Mato Grosso state (b) Paraná (c) Goiás (d) Rio Grande do Sul (e) Mato Grosso do Sul.



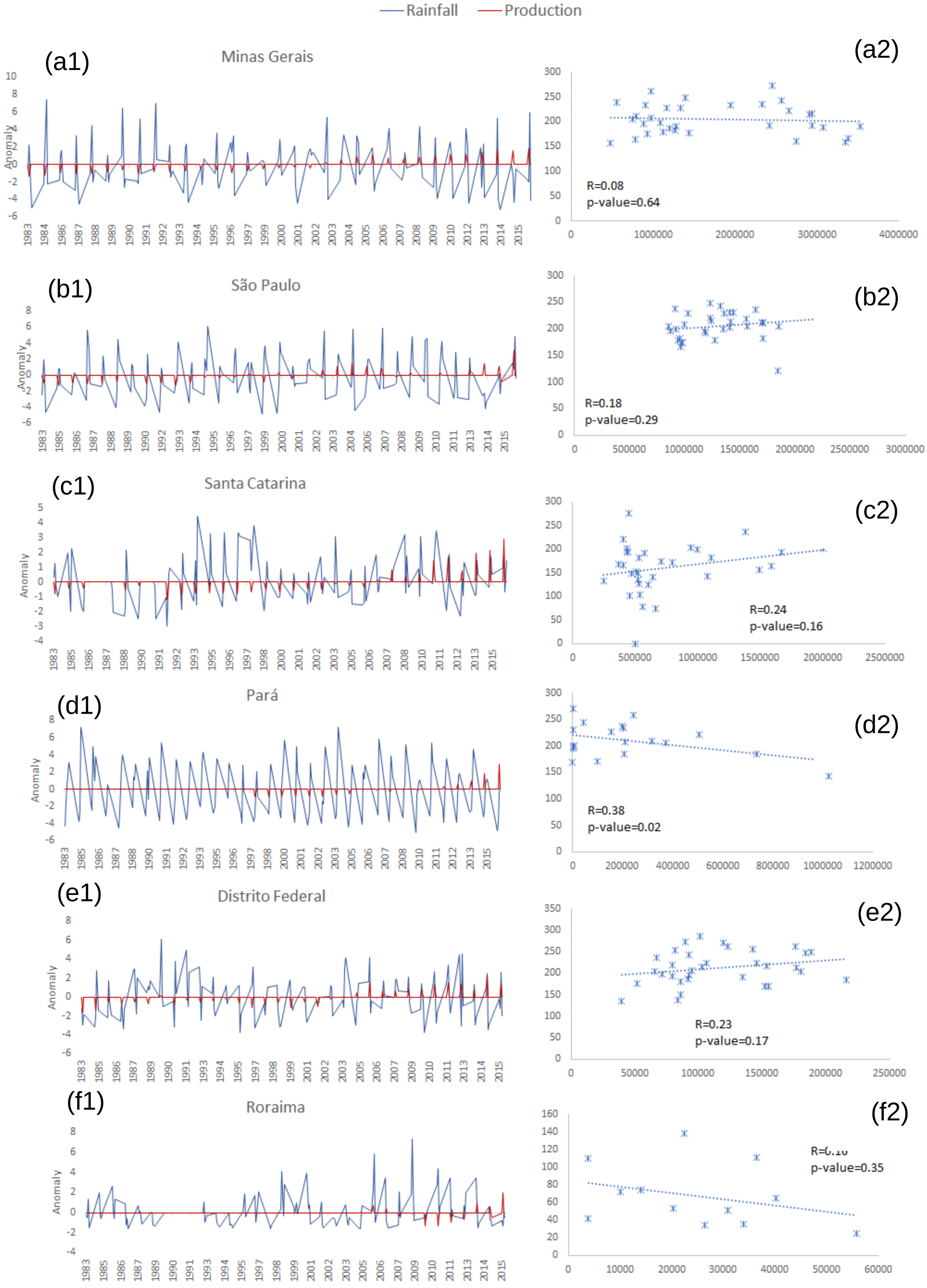
Source: The Author (2019).

Figure 15 - Precipitation and production anomalies of the MATOPIBA from 1983 to 2016 (a1) Maranhão (a2) correlation of Maranhão state (b) Tocantins (c) Piauí (d) Bahia.



Source: The Author (2019).

Figure 16 - Precipitation and production anomalies of the other states from 1983 to 2016 (a1) Minas Gerais (a2) correlation of Minas Gerais state (b) São Paulo (c) Santa Catarina (d) Pará (e) Distrito Federal (f) Roraima.



Source: The Author (2019).

The anomalies results showed that the year 1989 was extremely dryness, compared to the previous two years, practically all the studied states were affected, except Roraima (Fig 16f1) because the data is incomplete, this result can be due to the La Niña effect, according to Sanches et al. (2014), which is the abnormal cooling of the waters of the Pacific Ocean, being the opposite of El Niño. Already the decade 90's was the one that had most events of extreme drought, possibly due to the El Niño phenomenon, which in turn, causes the increase of the temperature of the waters and brings several consequences for the climate. According to Halpert et al. (1996) from 1990 to 1995 it was considered the longest El Niño event in the last 50 years, being comparable with the episode from 1911 to 1915 which disturbed soybean production practically in all states, as shown in Figures 14, 15 and 16. For example, in 1991, Santa Catarina state (Figure 16c1) with a production value of -1.14, Paraná (Fig. 14b1) with -1,14 and Rio Grande do Sul (Fig. 14d1) with -1,46 the lowest value obtained during all the study years.

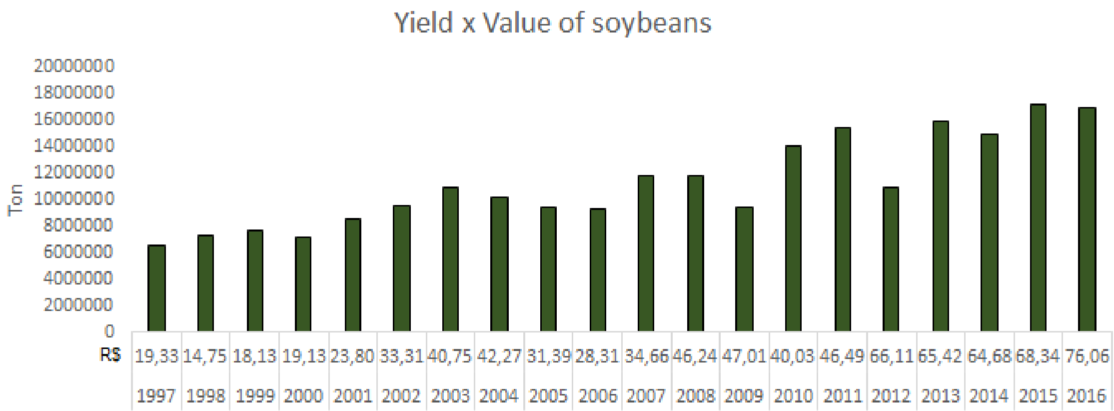
In the negative anomalies of 2001/2002, there was an extension of the drought period of the late 1990s, during which there was a truce in the year 2000. According to CEPED (2013), the São Francisco River suffered from the worst shortage and rains in history, caused by the drastic decrease in the volume of its waters, and to worsen the lack of rainfall throughout Brazil, prolonged drought. Climatologically summer is the rainiest season in the South, Southeast and Center-West of Brazil. However, during the summer of 2001/2002, there increase of negative precipitation anomalies trends in these regions (South, Southeast and Central West) affected by the soybean production, as shown in figures 14 and 16. The state in which it obtained a soybean production lower than the other states was Distrito Federal (Fig. 16e1), obtaining -0.9. Followed by Pará (Fig. 16d1) with -0.8, Tocantins (Fig. 15b1) with -0.5 and Santa Catarina (16c1) with -0.4.

In 2004/2005 negative anomalies trends were observed for Rio Grande do Sul (Fig. 14d1) obtaining -1.1 and Santa Catarina (Fig. 16c1) obtaining -1,5, in which there was a decrease in soybean yield due to precipitation and possibly Catarina phenomenon, which occurred in March 2004, bringing losses to soybean crops, among others. In 2007, according to CEPED (2013), northern Minas Gerais had the worst drought in history, with below-average rainfall, as can be observed in Figure 16a1, in which in 2007 there was a negative precipitation anomaly obtaining

-1.8, affecting soybean production in this period.

There was a total depression in agriculture in 2012, with the worst drought of the last 30 years, with a negative precipitation anomalies trend on soybean production in all states. Mainly in the state of Rio Grande do Sul (Fig. 14d1) obtaining a value of -0.2, São Paulo (Fig.16b1) with a value of -0.1 and Paraná (Fig. 14b1) obtaining 0.66 for soybean production anomalies respectively. A survey released by the Department of Rural Economy (Deral) of the Secretariat of Agriculture and Supply of Paraná, shows that the 2011/2012 soybean crop had a decrease in productivity, when compared to the previous harvest. Figure 17 shows the reduction of soybean production in the year 2012 and the increase in the value, in reais (R$), of the 60kg bag in the same year, indicating that drought influences the value of soybeans. This graphic was made for this state only because the Center for Advanced Studies in Applied Economics (CEPEA) has available data only for it.

Figure 17 - Relationship between production and value of soybeans for the state of Paraná.



Source: CEPEA (2019).

Figure 16 shows the trend of negative anomalies in most of the Southeast region, especially in Minas Gerais (Fig.16a1) and São Paulo (Fig.16b1), where the Cantareira system is located, in which, according to Marengo et al. (2005), rain values were very high lower than the histological average, being the lowest since 1961. The impacts of drought, as can be seen in negative precipitation anomalies and negative soybean production were enormous. The global loss was estimated at 5 billion, making it the 5th most expensive natural disaster in the world, affecting mainly agriculture. According to the Secretariat of Agriculture and Supply of the state of São Paulo, grain harvest in this harvest was 6.1 million tons, which represented a decrease of 20.1% in relation to the previous year, due to the climatic anomaly, in the which influenced productivity.

According to CEPED (2013), the lack of rain from mid-2011/2012 meant losses of up to 23.7% in production. This crop had a drop of more than 5 million tons compared to last season when Brazil recorded a record of production of the oilseed, amid the occurrence of the phenomenon La Niña, generating significant changes in precipitation patterns.

Currently the soybean is the main agricultural crop of MATOPIBA, according to EMBRAPA (2018) the newest agricultural frontier in Brazil is the MATOPIBA region, which is a continuous zone formed by the states of Maranhão, Tocantins, Piaui, and Bahia, located mostly with in the Cerrado biome. In this region, infrastructure is poor, land prices are cheap, and the climate and topographic relief are favorable for agriculture. Figure 15 shows the correlation between precipitation anomalies and soybean production of the MATOPIBA, in which it is possible to see a variation of precipitation anomalies and consequently in soybean production, highlighting the year 2012 in which production was low for all MATOPIBA states. According to studies CEPED (2015), Piauí (Fig. 15c1) and Bahia (Fig. 15d1) had soybean crop losses due to drought in 2014, obtaining values of production anomalies -1.1 and 1 respectively, which affected 50% of the grain production in the states. Maranhão (Fig. 15a1) and Tocantins (Fig. 15b1) are the only ones in the MATOPIBA region that have survived the drought season, with production anomalies of 1.9 and 2.3 respectively. The favorable climate for the soybean harvest is unfavorable to the development of the crop. In this way, the climate can be the limiting factor in the search for productivity gains.

4.2 NDVI INFLUENCE

The relationships between precipitation and vegetation indices provide a better insight into the onset and severity of drought (BAJGIRAN et al., 2008). The mean values of NDVI analyzed correspond to the location of soybean production for each state, and its correlation with the precipitation anomaly data were examined. Figure 16 shows a graph from the mean values of NDVI of the AVHRR and MODIS sensors, in the case the AVHRR the temporal resolution is sensor is determined per year and MODIS monthly in each year of the temporal series. The years choice for the vegetation indices coincided with the extreme drought months of precipitation anomalies. As can be seen (Fig. 18), both graphs of the AVHRR sensor and the MODIS have the same behavior, according to the linear regression.

In order to study the statistical relationships between various time lag periods and NDVI, Pearson correlation analysis was performed and correlation coefficients (*r* values) between the values of NDVI and precipitation anomalies data were determined. The results of such correlations are presented in Appendix B and C, which in turn, indicated that for NDVI, the significant correlation was found considering more than half states (Roraima, Santa Catarina, São Paulo, Paraná, Minas Gerais, Goiás, Distrito Federal, Mato Grosso do Sul, Mato Grosso, Bahia, Maranhão, Tocantins and Pará). For example, the state of Rio Grande do Sul (Fig. 19), between 1985 and 1991 obtained a lower threshold, reaching extreme drought (-1.64 for the precipitation anomaly data) and for the NDVI data it obtained a decrease of the index, reaching 0.59 in 1991 and considering the other drought years also there was change in the NDVI pattern. The year 2012 registered the lowest value of NDVI, reaching 0.53, being able to see clearly that the values of NDVI corresponded well to the precipitation. Scatter plots showing the correlation between values are also included, the correlation coefficient (*R*) for this relation was determined to be 0.61 (significant at a 95% confidence level), which indicates a moderate linear relationship between the four-month rainfall and NDVI. In general, the variables are moderately correlated, as shown in the appendix C, only the state of Piauí had a very low correlation value, obtaining the value of 0.01, possibly because the lack of data.

Figure 18 - Average values of NDVI of the AVHRR and MODIS sensors of the top five soybean production state (a) Mato Grosso (b) Paraná (c) Goiás (d) Rio Grande do Sul (e) Mato Grosso do Sul.

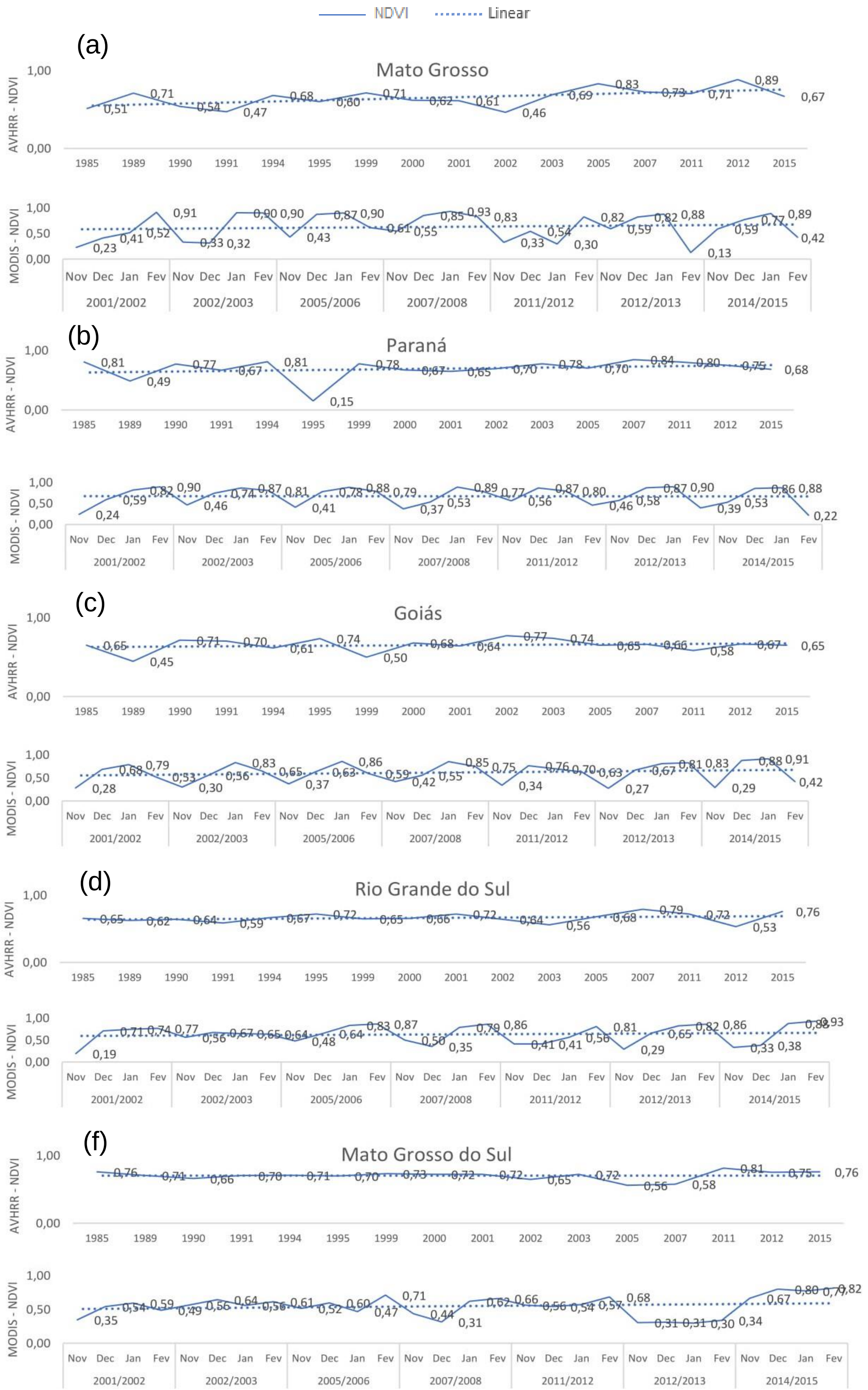
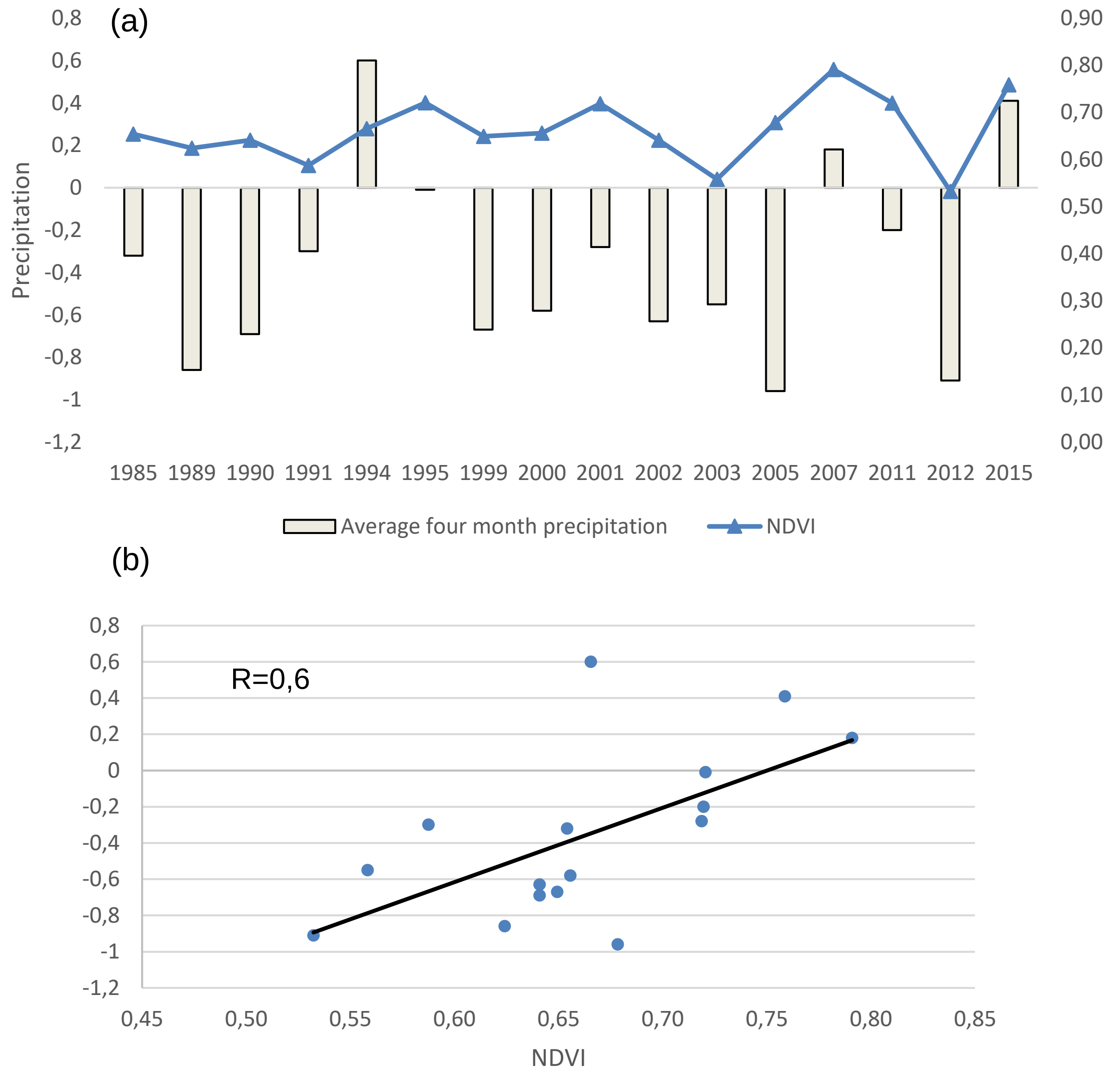


Figure 19 – (a) Average NDVI versus average four-month precipitation in Rio Grande do Sul state (b) The correlation between them.

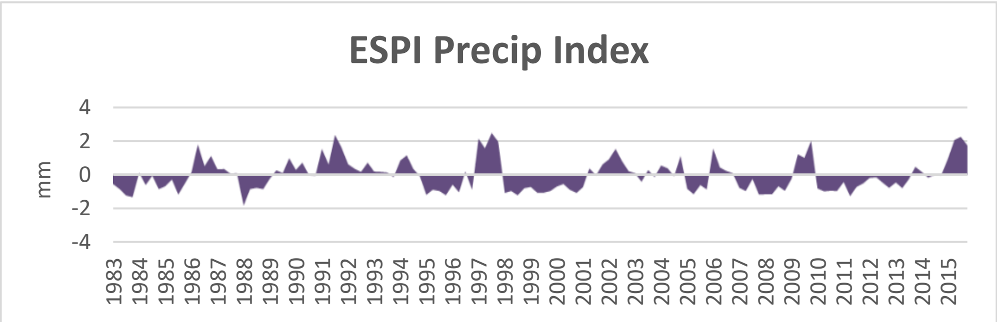


Source: The Author (2019).

Barbosa (1998) used monthly average rainfall and NDVI data to show that the spatial and temporal distributions of these two variables in north-east Brazil share common patterns and have a considerable degree of interdependence. Vegetation and climate are closely correlated with each other (WALTER & LIETH, 1967; WOODWARD et al., 2004). On the one hand, climate is the main limitation to vegetation growth, with the distribution of vegetation being highly influenced by climate (MATTHEWS, 1983). Batista et al. (1997), in their study have found that the NDVI annual compositions showed a clear and noticeable reduction during the dry years related to ESPI events in Brazil. Although, Liu et al. (1991) noticed that for most of the regions, the NDVI takes that the distribution of vegetation with stress corresponds to areas with occurrence of El Niño related droughts. Therefore, although the variations in vegetation indices can help to understand the effect of climatic factors on local vegetation cover, the variations will be of little practical value when planning for large-scale mitigation plans.

Figure 20 shows the ESPI indices time graph of the annual values from 1983 to 2016. For the annual values, the monthly values presented in this study were obtained, in which the months of November, December, January and February were obtained. Through the results of precipitation anomalies, it is possible to observe the extreme drought months (1985, 1989, 1990, 1991, 1994, 1995, 1999, 2001, 2002, 2005, 2007, 2011, 2012 and 2015), correlating with the events of ESPI shows that in 1985 the value of the index in the months studied were all negative, reaching -0.29mm in November. In 1988/89 obtained the lowest value of the event registered -1.85mm, in 1990 to 1994 the ESPI obtained positive values, already in 1995 the ESPI presents negative values, reaching -1,23mm. Positive values in the following years up to the year 1998, already in year 1998/99/00/01 negative values occurred, reaching -1,22mm. In its turn, in 2007, when it obtained a negative precipitation anomaly, there were also negative values of ESPI for that year, registering -1.18 mm. In the years 2011/12, negative values of ESPI were also recorded, reaching -1.29mm. Through this relationship between precipitation anomalies and ESPI it is possible to observe that whenever ESPI obtains negative values it generates significant changes in precipitation patterns and directly influence on soybean crop production.

Figure 20 - Time series graph of the annual values from 1983 to 2016 to present the set of ENSO indices.



Source: Adapted ESPI from NOAA/ESRL (2018).

5 CONCLUSIONS AND RECOMMENDATIONS

This research presented drought in agriculture through severity and duration through precipitation anomalies, as well as evaluate the effectiveness and relationship of these indicators with national soybean production data and finally evaluate the impacts of agricultural drought on soybean production areas. The results of the anomalies pointed out the existence of great pluviometric variability throughout Brazil, registering events considered extremely dryness, during consecutive years (1985, 1989, 1990, 1991, 1994, 1995, 1999, 2001, 2002, 2005, 2007, 2011, 2012 and 2015), it was possible to observe that precipitation anomalies responded moderately to soybean production.

Drought years indicates that the period from 1985 to 1999 showed drought largely with lower negative anomalies, highlighted for the years 1992 to 1994, in which consecutive droughts occurred, it could observe that the month of November is the one that suffers most from drought, exactly the month of soybean growth. While the period from 2003 to 2010 was more wet with positive anomalies, mainly in the month of January. The period from 2011 to 2016 showed a mixture of wet and dry years. It was found that the occurrence of positive anomalies was slightly higher than the negative, but during soybean growth an extreme drought can be expected every 2 to 4 years. It was analyzed the relationship between precipitation deficits in the months of soybean production and cultivation, together with ESPI events and the NDVI vegetation index.

Thus, it is possible to verify an occurrence, in soybean producing states, when there are extreme periods of agricultural drought and to relate to the ESPI events, in which it was possible to observe that when the ESPI registers negative values, there is a change in precipitation patterns. The next step was to correlated these data with the vegetation, for establish a statistically significant relationship between NDVI and precipitation, which, in turn, the scatter plots showed that precipitation anomalies values responded moderately to soybean production. The results shows a positive relationship between the two variables in most of the studied states, but in the states of Piauí, Pará, and Roraima, it is possible to see that there is a negative relationship of the variables, may be due to the lack of information on the studied years for both precipitation and grain yield. In addition, was also observed that both graphs, of the AVHRR sensor and the MODIS, have the same behavior, according to the straight equations resulting from the linear regression.

According to the research, it is remarkable that extreme drought impacts the soybeans production which in turn affects its commercial value. For example, the year 2012, Rio Grande do Sul state registered the lowest value of NDVI, reaching 0.53, also obtained a trend negative soybean production, obtaining a value of -0.91, being able to see clearly that the values of NDVI responded well to the precipitation and soybean production. It was compared the years of negative precipitation anomalies under the influence of the ESPI phenomenon, in the years 2011/12, negative values of ESPI were also recorded, reaching -1.29mm, it is possible to observe that whenever ESPI obtains negative values it generates significant changes in precipitation patterns and NDVI, consequently influencing soybean production.

This research provides a spatial and temporal perspective of the agricultural drought, involving different index derived from satellites. Thus, objective information on agricultural drought plays a key role in prioritizing the areas of soybean development and implementation of long-term mitigation measures.

The impact of drought assessment using other indexes concerning early warning in agriculture are some of the issues that still could be addressed as recommendation for future research as well as the use of rainfall data from Tropical Rainfall Measuring Mission (TRMM) and total water storage detected by Gravity Recovery and Climate Experiment (GRACE).

REFERENCES

ALVARES, C. A., STAPE, J.L., SENTELHAS, P.C., GONÇALVES, J. L. M., SPAROVEK, G. Koppen's climate classification map for Brazil. **Meteorologische Zeitschrift**, v. 22, n. 6, p. 711–728, 2014.

AN, K., OUYANG, Y. Robust grain supply chain design considering post-harvest loss and harvest timing equilibrium. Transportation Research Part E: **Logistics and Transportation Review**, v. 88, p. 110-128, 2016.

AWANGE, J. L.; MPELASOKA, F.; GONÇALVES, R. M. When every drop counts: analisys of drought in Brazil for the 1901-2013. **Science of the Total Everironment**, v. 566-567, p. 1472-1488, 2016.

AWANGE, J. L.; ALUOCH, J.; OGALLO, L. A.; OMULO, M.; OMONDI, P. Frequency and severity of drought in the LakeVictoria region (Kenya) and its effects on food security. **Climate Researsh**, v. 33, p. 135-142, 2007.

BAJGIRAN, P. R., DARVISHSEFAT, A. A., KHALILI, A., & MAKHDOUM, M. F. Using AVHRR-based vegetation indices for drought monitoring in the Northwest of Iran. **Journal of Arid Environments**, v. 72(6), p. 1086-1096. 2008.

BARBOSA, H. A. **Spatial and temporal analysis of vegetation index derived from AVHRR/NOAA and rainfall over Northeastern Brazil during 1982–1985**. Master degree dissertation in Remote Sensing [in Portuguese]. Divisão de Sensoriamento Remoto, Instituto Nacional de Pesquisas Espaciais, São José dos Campos, Brazil. 1998.

BATISTA, G.T., SHIMABUKURO, Y.E., LAWRENCE, W.T. The long-term monitoring of vegetation cover in the Amazonian region of northern Brazil using NOAA-AVHRR data. **International Journal of Remote Sensing**, v. 18, p. 3195–3210.1997.

BERLATO, M.A. AND CORDEIRO, A.P.A. **Climate variability and agriculture of Rio Grande do Sul**. In Droughts and losses in agriculture - a natural phenomenon or imprevidence? (Nascimento, A.M.N., Silveira Filho, I.L., Berton, A.L. e outros, eds.). Federacite, Porto Alegre, Brasil, p. 43-58, 2005.

BLAIN, G.C. Monthly values of the standardized precipitation index in the State of São Paulo, Brazil: trends and spectral features under the normality assumption.

Bragantia, v. 71, p. 122–131, 2012.

BOKEN, V. K; ARTHUR P. CRACKNELL, AND RONALD L. HEATHCOTE. **Monitoring and predicting agricultural drought: a global study**. Oxford University Press, 2005.

BRASIL. Ministry of Agriculture, Livestock and Supply. **Soybean**. Brasília, 2015. Available at: {http://www.agricultura.gov.br/vegetal/culturas/soja}. Accessed on: 25 Jun 2015.

CAMPBELL, J. B. **Introduction to Remote Sensing**. The Guilford Press, New York, v. 34, n. 1, p. 70, 1987.

CEPEA - **Center for Advanced Studies in Applied Economics.** University of São Paulo (USP). Sao Paulo – SP, 2019. Available at:\url{https://www.cepea.esalq.usp.br

/br/indicador/soja.aspx}. Accessed on: 25 May 2019.

CEPED - UNIVERSITY CENTER FOR DISASTER STUDIES AND RESEARCH. Federal University of Santa Catarina (CEPED/UFSC). **Brazilian Atlas of Natural Disasters 1991 to 2012**. Florianópolis – SC, p. 165, 2013.

CEPED - UNIVERSITY CENTER FOR DISASTER STUDIES AND RESEARCH. Federal University of Santa Catarina (CEPED/UFSC). **Brazilian Atlas of Natural Disasters 1994 to 2015**. Florianópolis – SC, p. 95, 2013.

CHOUHAN, R. AND RAO, N. Vegetation Detection in Multispectral Remote Sensing images: Protective Role-Analysis of Vegetation. **Indian Ocean Tsunami**. PDPM Indian Institute of Information Technology, 2017. Available at: \url{http://www.isprs.org/proceedings/2011/gi4dm/pdf/op37.pdf}. Acessed on: 07 nov 2017.

COHEN, J. **Statistical power analysis for the behavioral sciences**. Routledge, 2013.

CONAB (NATIONAL SUPPLY COMPANY). **Eighth survey of grain harvest 2011/2012**. In Compendio de estudos conab, v. 1, p. 35, 2012.

CONAB. **Follow-up brazilian grain harvest 2014/15**. In Seventh survey, Brasília, v. 2, p. 1-100, 2015.

CONAB. **Soyabean productivity**: analysis and perspectives. In Compendio de estudos conab, v. 1, p. 35, 2016.

CONTI, J. B.; FURLAN, Sueli Angelo. Geoecologia: o clima, os solos e a biota. In: **Geografia do Brasil** [S.l: s.n.], Edusp, São Paulo, p. 67–208, 2011.

CURTIS, S., AND ADLER, R. ENSO indices based on patterns of satellite-derived precipitation. **Journal of Climate**, v. 13, p. 2786-2793, 2000.

DE NYS, E., ENGLE, N.L., MAGALHÃES, A.R. **Droughts in Brazil: proactive policy and management**. Brasília, DF: Center for Management and Strategic Studies – CGEE, World Bank, p. 590-605, 2016.

DA SILVA JUNIOR, C. A., LIMA, M., JOHANN, J. A., ROSSI, F. S., DE OLIVEIRA, JUNIOR, J. F., JUNIOR, A. H. S. L., PALUDO, A., BECKER, W. R., DO NASCIMENTO, K. R., ZANIN, R. B. SOJAMAPS: project of monitoring of soybean areas in Brazil using big data in the cloud computing. **In anais**: XIX Simpósio Brasileiro de Sensoriamento Remoto. Santos, São Paulo, 2019.

DOSS, B. D., R. W. PEARSON, AND HOWARD T. ROGERS. Effect of Soil Water Stress at Various Growth Stages on Soybean Yield. **Agronomy jornal,** v. 66, p. 297-299, 1974.

EMBRAPA (BRAZILIAN AGRICULTURAL RESEARCH COMPANY). **No-till simplification reduces crop efficiency,** 2015. Available at: \url{https://www.embrapa.br/en/busca-de-noticias/-/noticia/1909275/simplifcacao-do-plantio-diretoreduz-efciencia-da-lavoura}. Acessed on: 26 fev 2018.

EMBRAPA (BRAZILIAN AGRICULTURAL RESEARCH COMPANY). **Living with drought**, 2017. Available. at: \url{https://www.embrapa.br/tema-convivencia-com-a-seca}. Accessed on: 10 Oct 2017.

EMBRAPA (BRAZILIAN AGRICULTURAL RESEARCH COMPANY). **Vision 2030:** the future of Brazilian agriculture, 2018**.** Available at: \url{https://www.embrapa.br/visao/o-futuro-da-agricultura-brasileira}. Accessed on: 01 Mar 2018.

FAO (FOOD AND AGRICULTURAL ORGANIZATION OF THE UNITED NATIONS). **GIEWS - Global Information and Early Warning System**, 2015. Available at: \url{http://www.fao.org/giews/countrybrief/country.jsp?code=BRA}. Accessed on: 10

Oct 2017.

FARIAS, J.R.B., NEUMAIER, N., NEPOMUCENO, A.L. **Agrometeorology of crops**: the meteorological factor in agricultural production. In: 1. ed. Brasília: Inmet, p. 271-272, 2009.

FERNANDES, D. S., HEINEMANN, A. B., DA PAZ, R. L.; AMORIM, A. O., CARDOSO, A. S. Index for the Drought Quantification. Brazilian Agricultural Research Corporation. Embrapa Rice and Beans, Ministry of Agriculture, **Livestock and Food Supply**, Santo Antônio de Goiás-GO, p. 48, 2009.

GOIS, G., OLIVEIRA-JUNIOR, J.F., DELGADO, R.C., MORAES, M. Drought severity on Tocantins state and its relations with el nino events. **Enc. Biosfera,** v. 9, p. 1973–1989, 2013.

GOLLDACK, D., LUKING, I., YANG, O. Plant tolerance to drought and salinity: stress regulating transcription factors and their functional significance in the cellular transcriptional network. **Plant cell reports**, v. 30, p. 1383-1391, 2011.

GOPFERT, H., ROSSETTI, L. A.; SOUZA, J. DE. **Widespread events and agricultural security**, Brasília: IPEA, 1993.

HALPERT, M.S., BELL, G.D., KOUSKY, V.E., ROPELEWSKI, C. Climate Assessment for 1995. **Bulletin of American Meteorological Society**, v. 77(5), 1996.

HAO, Z., YUAN, X., XIA, Y., HAO, F., SINGH, V. P. An overview of drought monitoring and prediction systems at regional and global scales. **Bulletin of the American Meteorological Society**, v. 98(9), p. 1879-1896, 2017.

HENRICKSEN, B. L. AND DURKIN, J. W. Growing period and drought early warning in Africa using satellite data**. International Journal of Remote Sensing**, v. 7(11), p. 1583-1608, 1986.

IBGE (BRAZILIAN INSTITUTE OF GEOGRAPHY AND STATISTICS). **Automatic Recovery Data IBGE System,** 2015. Available at: \url{https://sidra.ibge.gov.br/Tabela/1612}. Accessed on: October 20, 2016.

IBGE (BRAZILIAN INSTITUTE OF GEOGRAPHY AND STATISTICS). **Brazil in synthesis. Rio de Janeiro: IBGE**, 2016. Available at: \url{https://ww2.ibge.gov.br/home/estatistica/populacao/estimativa2017/estimativa_ dou.html}. Accessed on: October 20, 2016.

KARABURUN, A. Estimation of C factor for soil erosion modeling using NDVI in Buyukcekmece watershed. **Ozean journal of applied sciences**, 2010. Available at: \url{http://ozelacademy.com/OJAS_v3n1_8.pdf}. Acessed on: 07 nov 2016.

KIDWELL, K. B. **NOAA Polar Orbiter Data User's Guide**. NOAA/NESDIS, Washington, D.C, 1991.

KLISCH, A. AND ATZBERGER, C. Operational drought monitoring in Kenya using MODIS NDVI time series**. Remote Sensing**, v. 8(4), p. 267, 2016.

KOGAN, F.N. Application of vegetation index and brightness temperature for drought detection. **Advances in Space Research**, v, 15(11), p. 91–100, 1995.

LI, W.; FU, R.; JUAREZ, R.I.N.; FERNANDES, K. Observed change of the standardized precipitation index, its potential cause and implications to future climate change in the Amazon region. **Philosophical Transactions of the Royal Society**, v. 363, p.1767– 1772, 2008.

LIMA, D.P., FIORIOLLI, J.C., PADULA, A.D., PUMI, G. The impact of Chinese imports of soybean on port infrastructure in Brazil: A study based on the concept of the “Bullwhip Effect”. **Journal of Commodity Markets**, v. 9, p. 55-76, 2017.

LIU, W.T., MASSAMBANI, O., FESTA, M. Normalized difference vegetation index for the south American continent used as a climatic variability indicator. **24th International Symposium of Remote Sensing of Environment,** Rio de Janeiro, 27–31 May 1991 (Ann Arbor: ERIM), p. 725–732, 1991.

LIU, W.T. AND NEGRÓN JUÁREZ, R.I. Enso drought onset prediction in Northeast Brazil using NDVI. **International Journal of Remote Sensing**, v. 17, p. 3483-3501, 2015.

MATTHEWS, E. Global vegetation and land use: new high-resolution data bases for climate studies. **Journal of Climate,** Appl. Meteorol, v. 22, p. 474–487, 1983.

MARENGO, J.A., C.A. NOBRE, J. TOMASELLA, M.D. OYAMA, G.S. OLIVEIRA, R. OLIVEIRA, H. CAMARGO, L.M. ALVES, AND F. BROWN. The drought of Amazonia in 2005. **Journal of climate**, v. 21, p. 495- 516, 2008.

MARIANO, D. A. **Detection and evaluation of agronomic drought through the**

analysis of time series of MODIS and PERSIANN data. Master's Dissertation. National Institute of Space Research, São José dos Campos. 86p, 2015.

MARIANO, D.A., SANTOS, C.A.C., WARDLOW, B.D., ANDERSON, M.C., SCHILTMEYER, A.V., TADESSE, T.; SVOBODA, M. D. Use of remote sensing indicators to assess effects of drought and human-induced land degradation on ecosystem health in Northeastern Brazil. **Remote Sensing of Environment**, v. 213, p. 129-143, 2018.

MCVICAR, T. R. AND JUPP, D. Using covariates to spatially interpolate moisture availability in the Murray–Darling Basin: A novel use of remotely sensed data, **Remote Sensing of Environment**, v. 79(2), p.199–212, 2002.

MISHRA, A.K. AND SINGH, V.P. A Review of Drought Concepts. **Journal of Hydrology,** v. 391, n. 1, p. 202-216, 2010.

MORANDO, R., SILVA, A.O., CARVALHO, L.C., PINHEIRO, M.P.M.A. Water deficit: effect on soybean crop. **Journal of agronomic sciences**, v. 3, p. 114-129, 2014.

MOREIRA, A.A. **Analysis of drought in the north of the state of minas gerais from modis data**. Masters dissertation. Federal University of Rio Grande do Sul. Postgraduate Program in Remote Sensing, Porto Alegre, 124f, 2016.

MPELASOKA, F., AWANGE, J. L., GONCALVES, R. M. Accounting for dynamics of mean precipitation in drought projections: A case study of brazil for the 2050 and 2070 periods. **Science of the total environment**, v. 622, p 1519-1531, 2017.

NDMC, National Drought Mitigation Center. **What is drought?**. University of Nebraska-Lincoln, 2006. Disponível em: \url{http://drought.unl.edu/DroughtBasics.as

px} Access em: 14 nov 2018.

NOAA. NOAA Earth System Research Laboratory. **Niño Southern Oscillation (ENSO)**, 2018. Available at: \url{https://www.esrl.noaa.gov/psd/enso/} Access em: 14 nov 2018.

NOIA JUNIOR, R.S. AND SENTELHAS, P. C. Soybean-maize off-season double crop system in Brazil as affected by El Niño Southern Oscillation phases. **Agricultural Systems**, v. 173, p. 254-267, 2019.

PANU, U. S. AND SHARMA, T. C. Challenges in drought research: some perspectives and future directions. **Hydrological Sciences Journal**, v. 47, n. S1, p. S19-S30, 2002.

PETERS, A. J., WALTER-SHEA, E. A., JI, L., VINA, A., HAYES, M., SVOBODA, M. D. Drought monitoring with NDVI-based standardized vegetation index. **Photogrammetric Engineering and Remote Sensing**, v. 68(1), p. 71-75, 2002.

PETTORELLI, N., VIK, J. O., MYSTERUD, A., GAILLARD, J. M., TUCKER, C. J., & STENSETH, N. C. Using the satellite-derived NDVI to assess ecological responses to environmental change. **Ecology & Evolution**, v. 20(9), p. 503-510, 2005.

PHILLIPS, O.L., ARAGÃO, L.E.O.C., LEWIS, S.L. Drought sensitivity of the Amazon rainforest. **Science**, v. 323, p.1344–1347, 2009.

SANCHES, F. O., VERDUM, R., FISCH, G. The rainfall anomaly index in the annual precipitation evaluation in Alegrete/RS (1928-2009). **Caminhos de Geografia**, v.15(51), p. 73-84, 2014.

SAUSEN, T. M. AND LACRUZ, M.S.P. **Remote sensing for disasters**. Oficina de Textos, São Paulo, 2015.

/SAI, M.V.R., MURTHY, C.S., CHANDRASEKAR, K., JEYASEELAN, A. T., DIWAKAR, P. G., DADHWAL, V. K. Agricultural drought: assessment & monitoring. **Mausam**, v. 67, p. 131-142, 2016.

SIONIT, N., & KRAMER, P. J. Effect of Water Stress During Different Stages of Growth of Soybean. **Agronomy Journal**, v. 69(2), p. 274-278, 1977.

SMIDERLE, O.J. **Soybean cultivation in the cerrado of Roraima**. Boa Vista, Embrapa Roraima, (Embrapa Roraima. Sistema de Produção, 1), 2009.

STUCK, J., A. GUNTNER, B. MERZ. ENSO impact on simulated South America hydroclimatology. **Geosciences**. v. 6. p. 227-236, 2006. Available at:{http://siste

masdeproducao.cnptia.embrapa.br/FontesHTML/Soja/CultivodeSojanoCerradodeRoraima/clima.htm}. Accessed on: 23 Jun 2018.

TADDEI, R. AND GAMBOGGI, A.L. **After the rain did not come. Social responses to droughts in the Northeast, Amazonia and in the south of Brazil**. Fortaleza, Brazil: FUNCEME / CIFAS, 2010.

TEODORO, P.E., CORREA, C.C.G., TORRES, F.E., DELGADO, R.C. Analysis of the Occurrence of Wet and Drought Periods Using Standardized Precipitation Index in Mato Grosso do Sul State, Brazil. **J. Agron**, v. 14, p. 80, 2015.

USGS (UNITED STATES GEOLOGICAL SURVEY). **MODIS/Terra Vegetation Indices 16-Day L3 Global 1 km SIN Grid**. Available at:{http:// https://lpdaac.usgs.gov/products/mod13a2v006/}. Accessed on: 23 Jun 2019.

WALTER, H. AND LIETH, H. **Climate diagram world atlas**. Fischer: Jena, Germany, 1967.

WARDLOW, B.D., ANDERSON, M.C., VERDIN, J.P. **Remote Sensing of Drought: Innovative Monitoring Approaches**. Boca Raton, FL: CRC Press, p. 484, 2012.

WILHITE, D, A. AND GLANTZ, M. H. Understanding the drought phenomenon: the role of definitions. **Water International**, v.10, n.3, p. 111-120, 1985.

WILHITE, D.A. **The role of disaster preparedness in national planning with specific reference todroughts**. Natural Disasters and Extreme Events in Agriculture (M.V.K. Sivakumar, R.P. Motha, and H.P. Das, eds.), Springer-Verlag, Berlin, Germany. p. 23-37, 2005.

WOODWARD, F.I., LOMAS, M.R., KELLY, C.K. Global climate and the distribution of plant biomes. Philos. Trans. R Soc. Lond. B: **Biol. Sci**, v. 359, p. 1465–1476, 2004.

Appendix A - Summary of the results of the regression statistic for the states of figure 12 (a) Mato Grosso (b) Paraná (c) Goiás (d) Rio Grande do Sul (e) Mato Grosso do Sul.

(a)

Summary of results (MATO GROSSO)

Regression Statistics	
Multiple R	0,55579
R Square	0,308902
Adjusted R Square	0,286609
Standard Error	7056159
Observation	33

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	-1,3E+07	6542840,53	-1,93783	0,0618	-26023103,97	665318,508
seansonal_mean	105960,8	28465,824	3,722387	0,000785	47904,37076	164017,232

(b)

Summary of results (PARANÁ)

Regression Statistics	
Multiple R	0,1344959
R Square	0,0180891
Adjusted R Square	-0,0135853
Standard Error	4119626,2
Observation	33

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	7348321,8	1371417	5,35819	7,69E-06	4551297,47	10145346,2
seansonal_mean	4359,6746	5768,991	0,75570	0,45552	-7406,2610	16125,6103

(c)

Summary of results (GOIÁS)

Regression Statistics	
Multiple R	0,0886682
R Square	0,0078620
Adjusted R Square	-0,0241424
Standard Error	2800521,4
Observation	33

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	6519775,1	4669095	1,39636	0,172523	-3002907	16042457
seansonal_mean	-9478,4254	19123,75	-0,49564	0,623647	-48481,6	29524,72

(d)

Summary of results (RIO GRANDE DO SUL)

Regression Statistics	
Multiple R	0,009499
R Square	9,02E-05
Adjusted R Square	-0,03216
Standard Error	3172833
Observation	33

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	6715941	1361989,80	4,93097	2,617E-0	3938145	9493737,91
seansonal_mean	476,0987	9001,42140	0,05289	0,958157	-17882,4	18834,6187

(e)

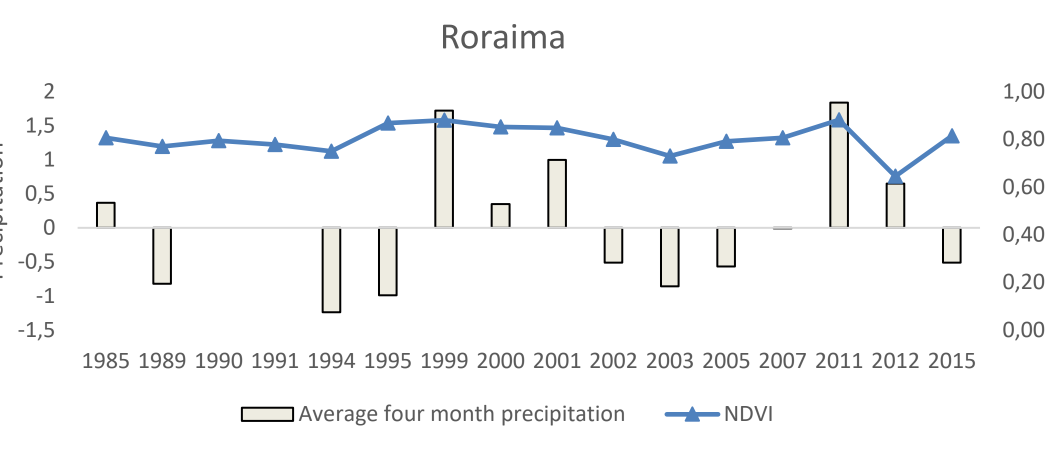
Summary of results (MATO GROSSO DO SUL)

Regression Statistics	
Multiple R	0,4055457
R Square	0,1644673
Adjusted R Square	0,1375147
Standard Error	1350133,7
Observation	33

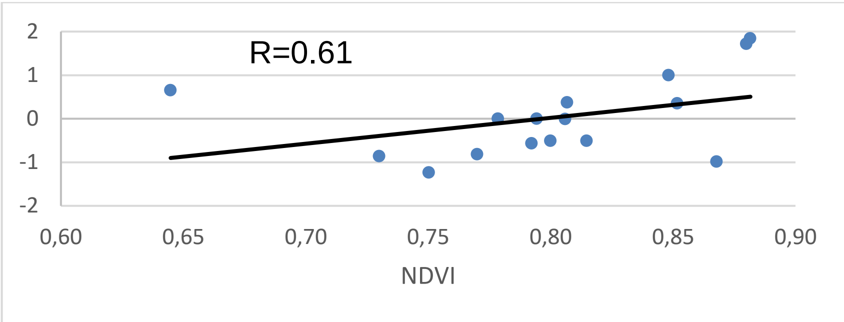
	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	2213621,2	512360,2	4,32044	0,000149	1168656	3258587
seansonal_mean	8029,7868	3250,611	2,47023	0,019208	1400,122	14659,45

Appendix B - (a) Average NDVI versus average four-month precipitation (b) The correlation between them.

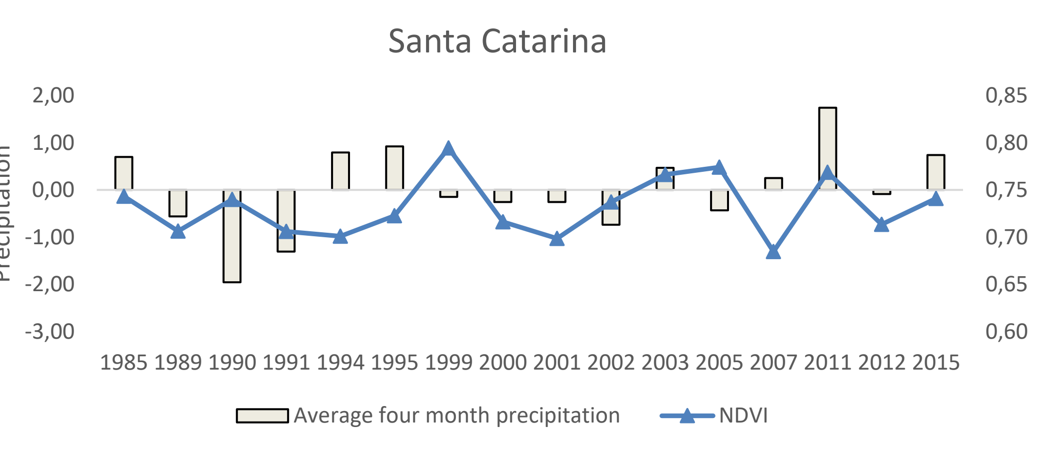
(a)



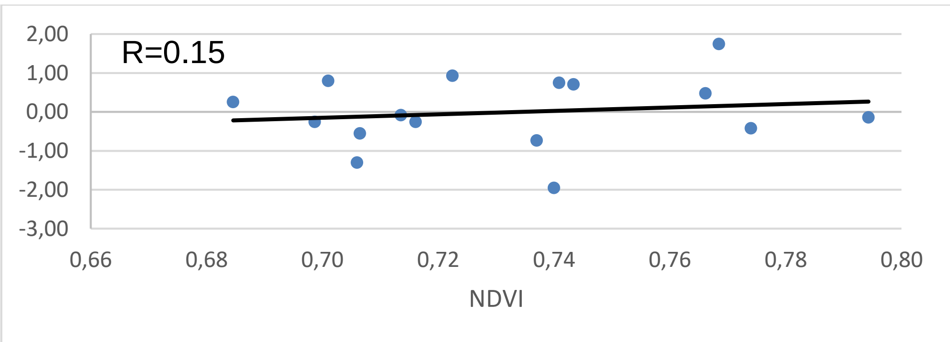
(b)

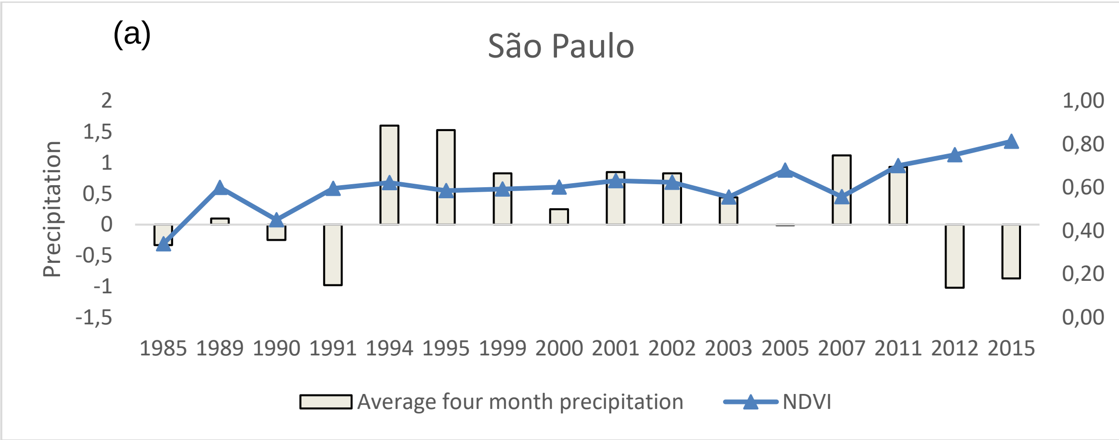


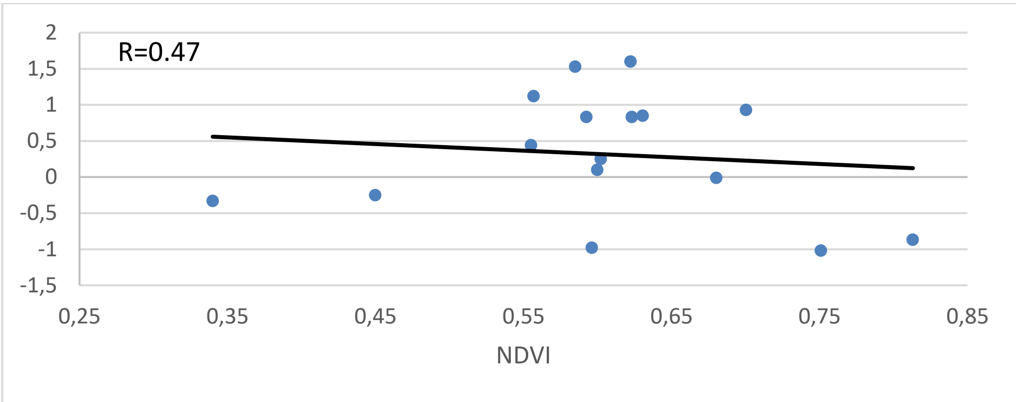
(a)

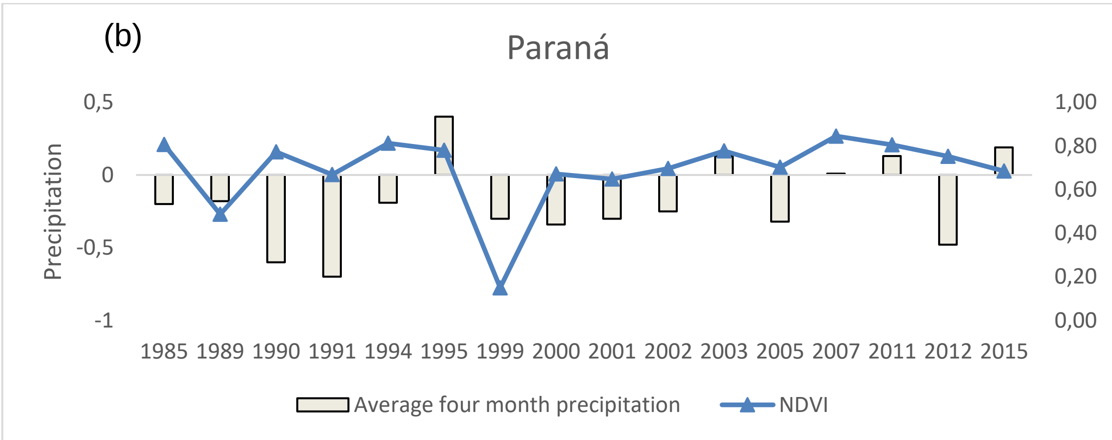


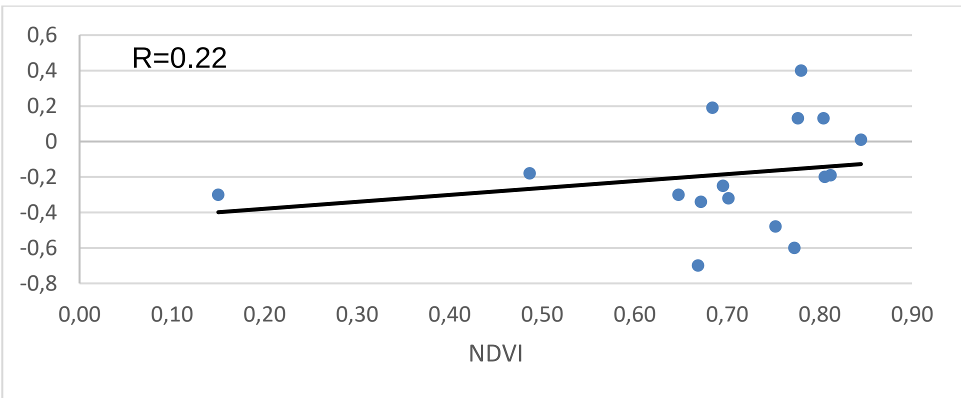
(b)

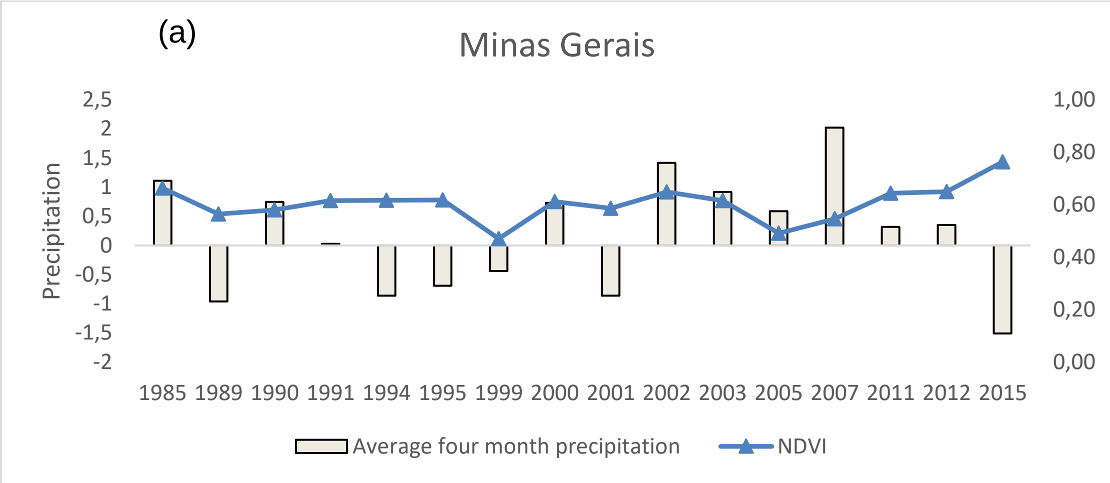


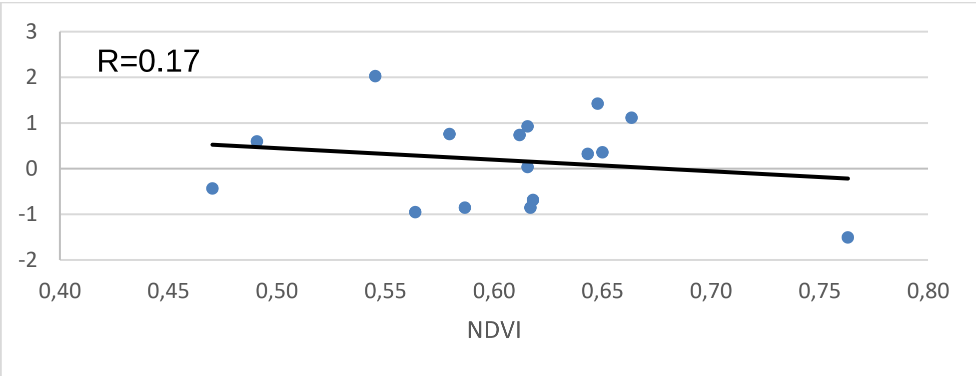

(a)
São Paulo
Precipitation
2
1,5
1
0,5
0
-0,5
-1
-1,5
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

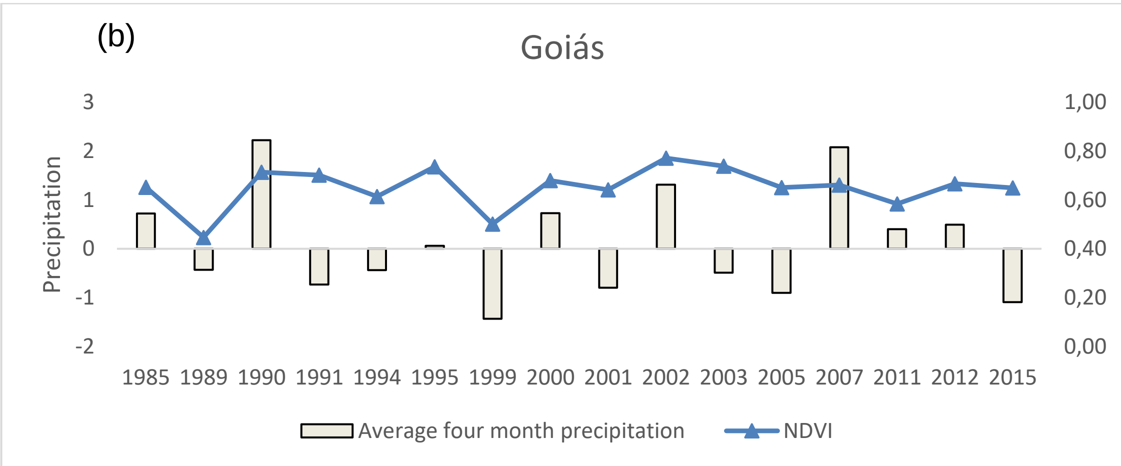

R=0.47
2
1,5
1
0,5
0
-0,5
-1
-1,5
0,25 0,35 0,45 0,55 0,65 0,75 0,85
NDVI

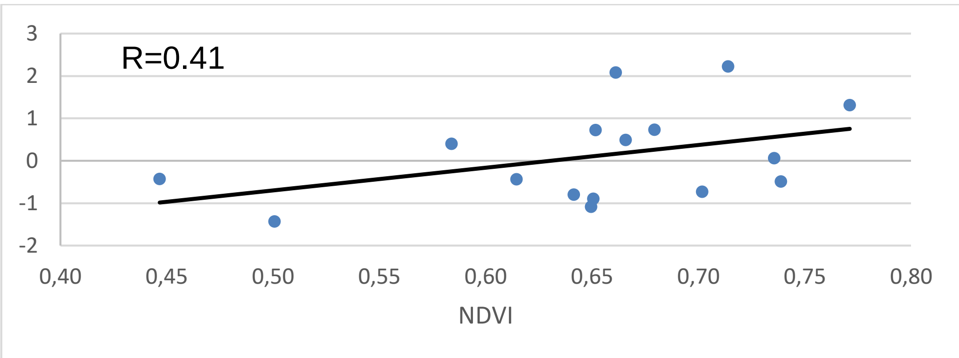

(b)
Paraná
Precipitation
0,5
0
-0,5
-1
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

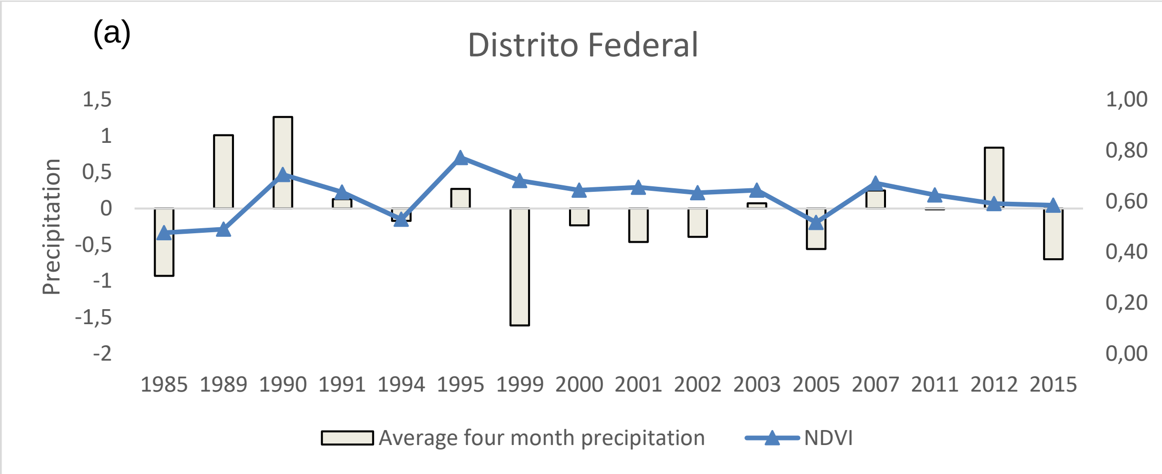

R=0.22
0,6
0,4
0,2
0
-0,2
-0,4
-0,6
-0,8
0,00 0,10 0,20 0,30 0,40 0,50 0,60 0,70 0,80 0,90
NDVI

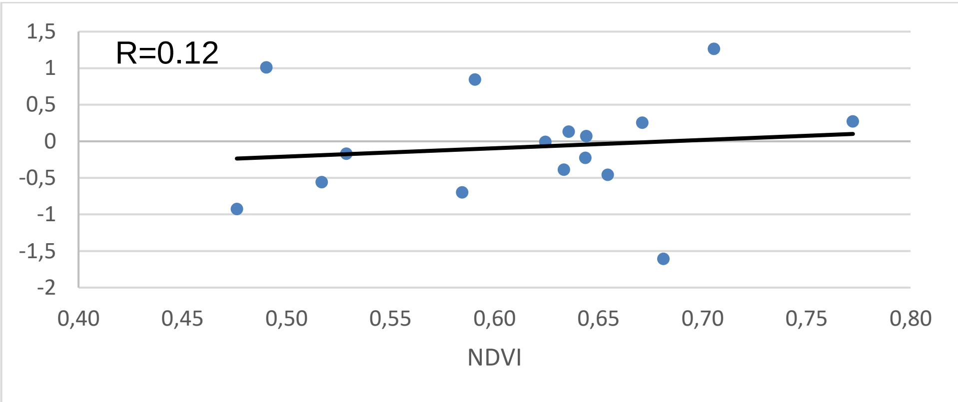

(a)
Minas Gerais
Precipitation
2,5
2
1,5
1
0,5
0
-0,5
-1
-1,5
-2
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

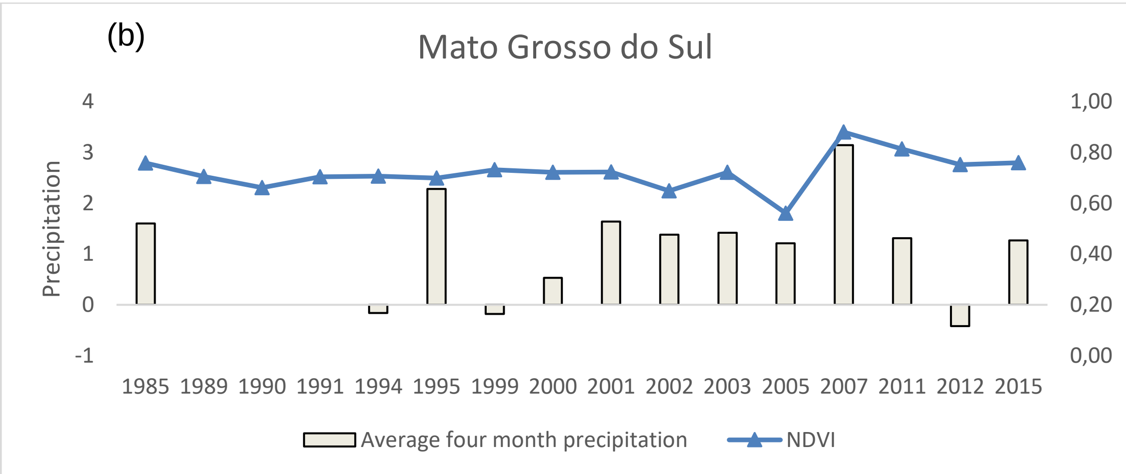

R=0.17
3
2
1
0
-1
-2
0,40 0,45 0,50 0,55 0,60 0,65 0,70 0,75 0,80
NDVI

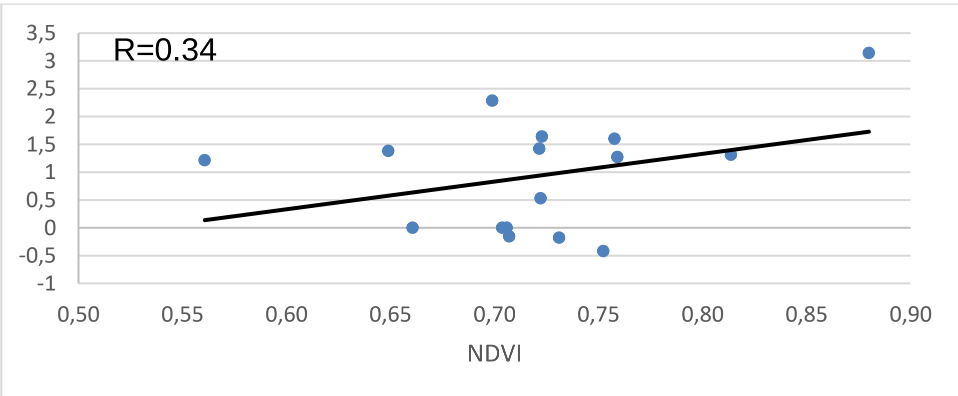

(b)
Goiás
Precipitation
3
2
1
0
-1
-2
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

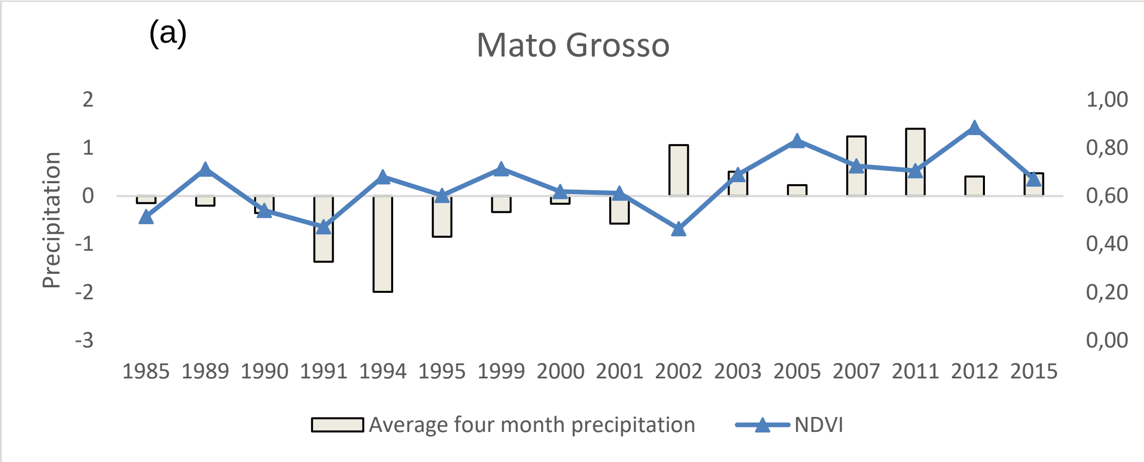

R=0.41
3
2
1
0
-1
-2
0,40 0,45 0,50 0,55 0,60 0,65 0,70 0,75 0,80
NDVI


(a)
Distrito Federal
Precipitation
1,5
1
0,5
0
-0,5
-1
-1,5
-2
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

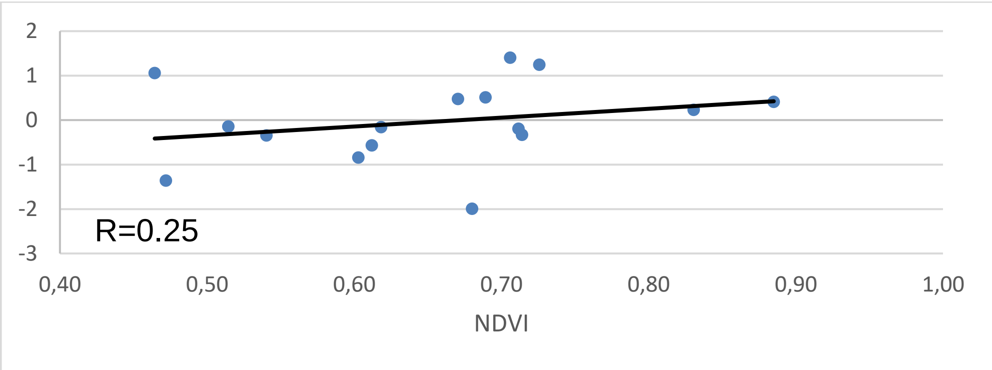

R=0.12
1,5
1
0,5
0
-0,5
-1
-1,5
-2
0,40 0,45 0,50 0,55 0,60 0,65 0,70 0,75 0,80
NDVI


(b)
Mato Grosso do Sul
Precipitation
4
3
2
1
0
-1
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

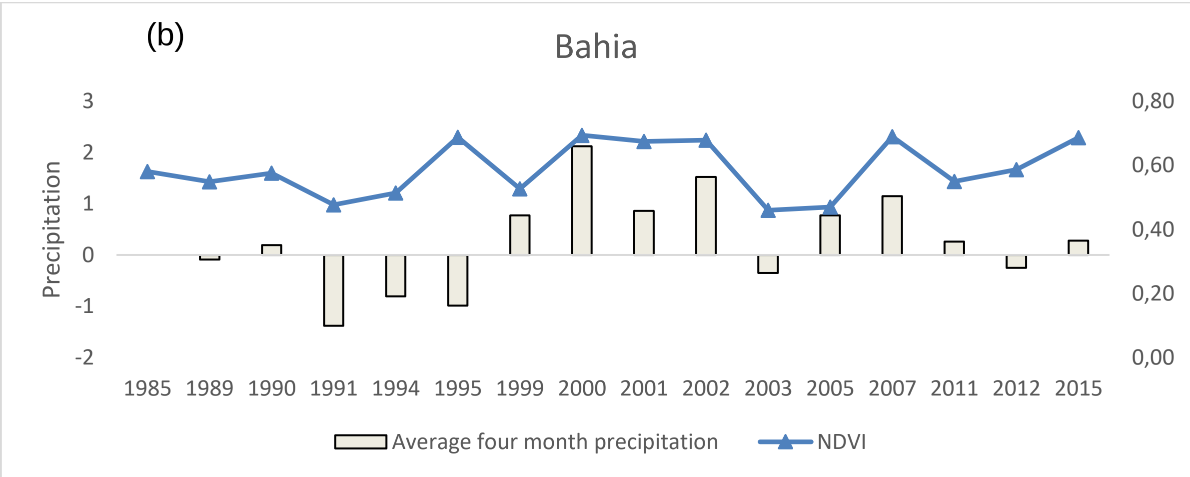

R=0.34
3,5
3
2,5
2
1,5
1
0,5
0
-0,5
-1
0,50 0,55 0,60 0,65 0,70 0,75 0,80 0,85 0,90
NDVI



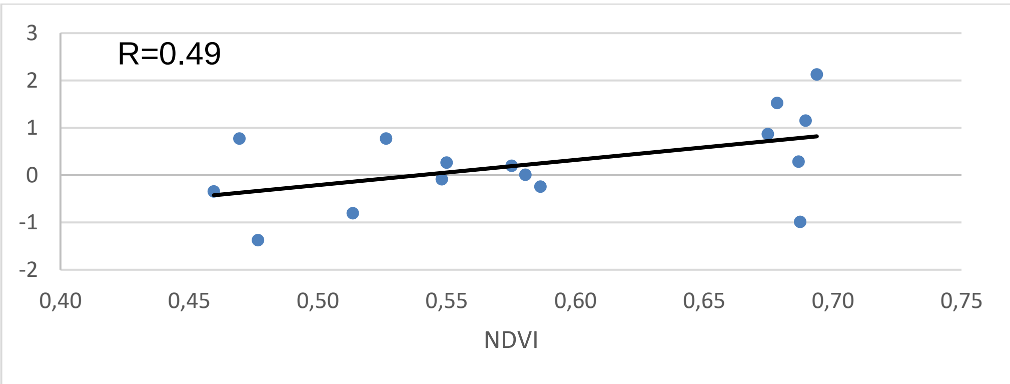
(a)
Mato Grosso
Precipitation
2
1
0
-1
-2
-3
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI



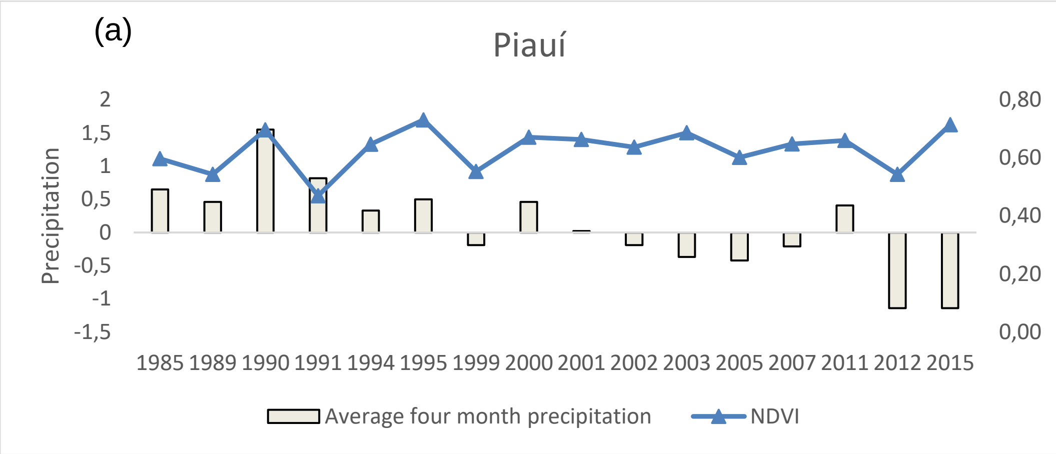
R=0.25
2
1
0
-1
-2
-3
0,40 0,50 0,60 0,70 0,80 0,90 1,00
NDVI

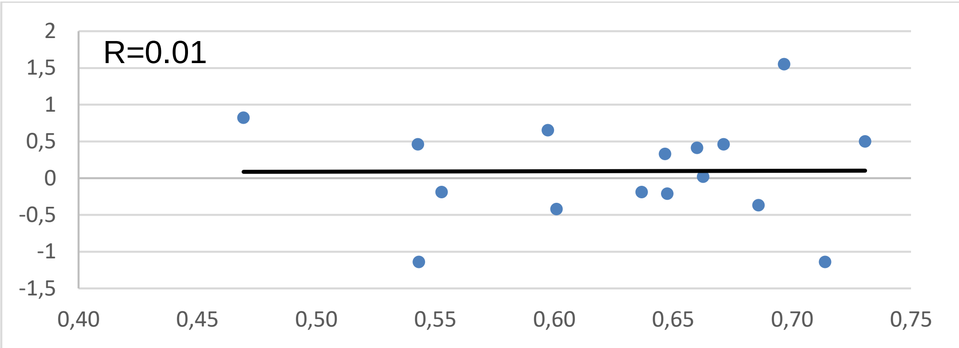


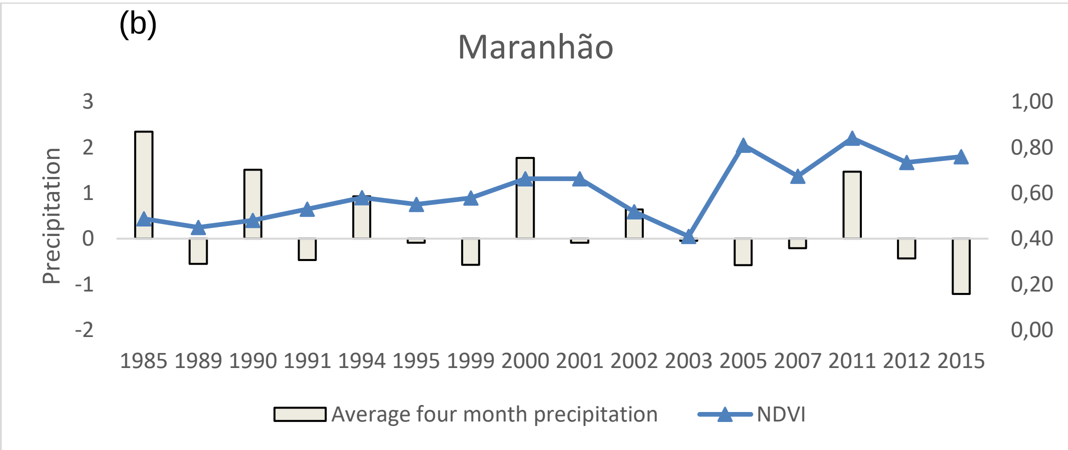
(b)
Bahia
Precipitation
3
2
1
0
-1
-2
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

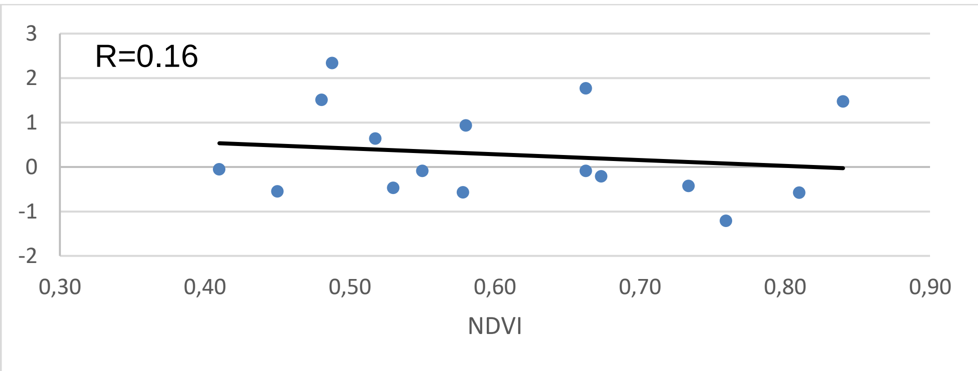


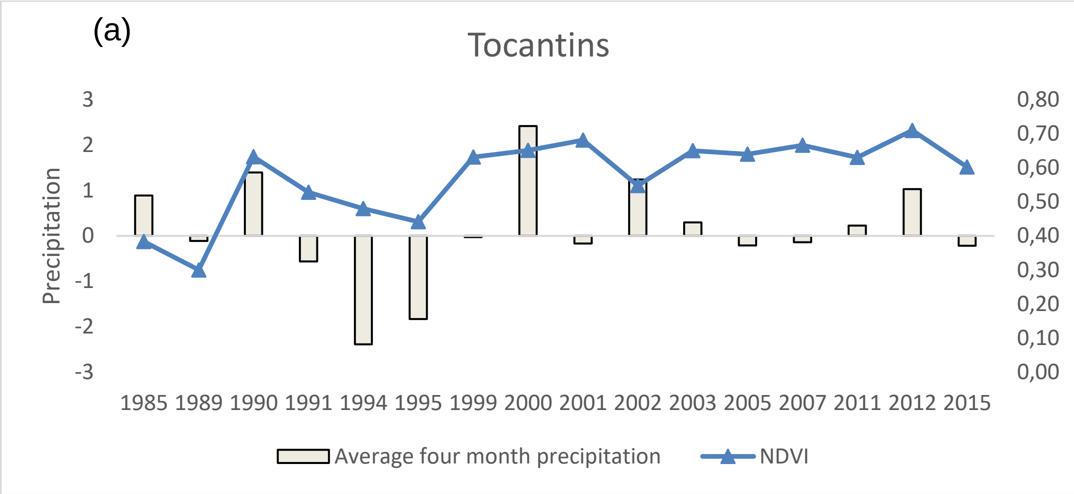
R=0.49
3
2
1
0
-1
-2
0,40 0,45 0,50 0,55 0,60 0,65 0,70 0,75
NDVI

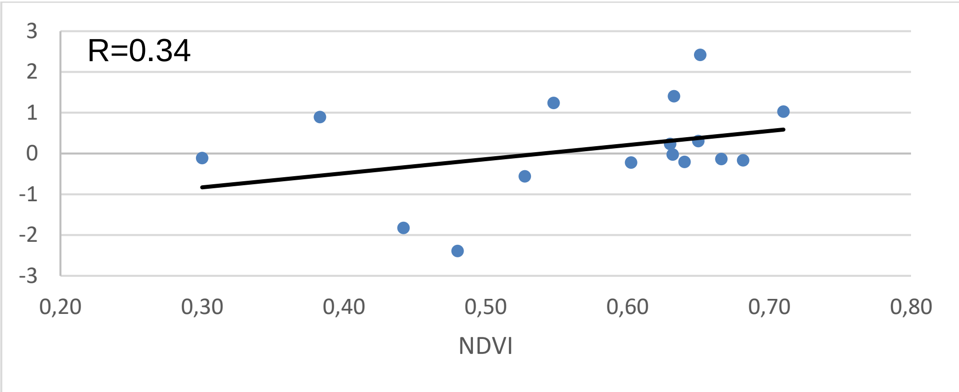

(a)
Piauí
Precipitation
2
1,5
1
0,5
0
-0,5
-1
-1,5
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI

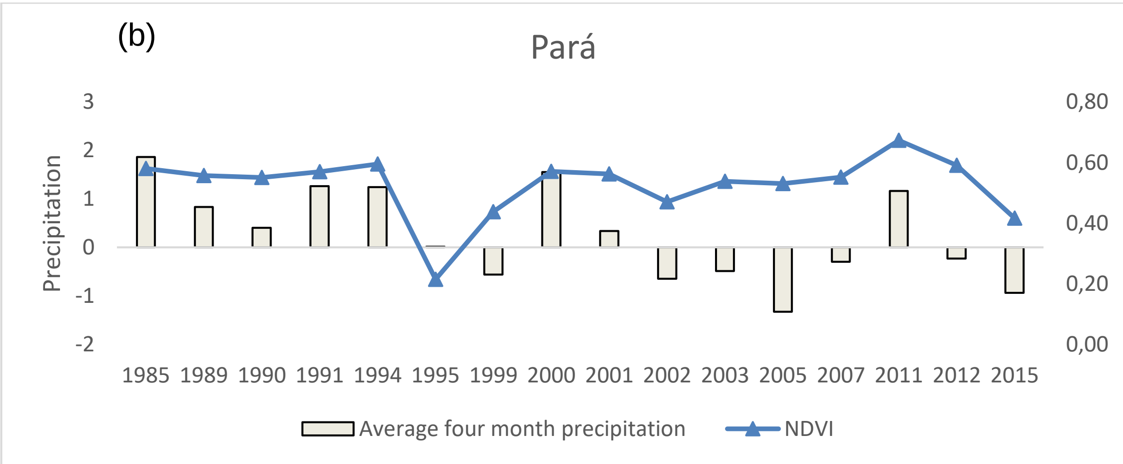

R=0.01
2
1,5
1
0,5
0
-0,5
-1
-1,5
0,40
0,45
0,50
0,55
0,60
0,65
0,70
0,75

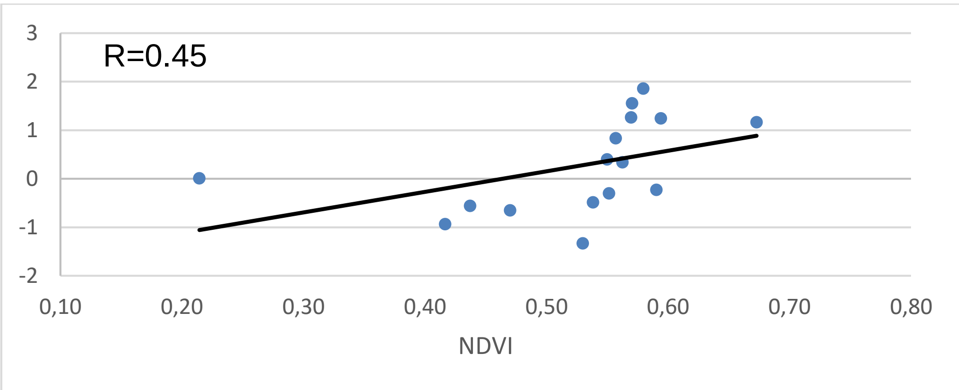

(b)
Maranhão
Precipitation
3
2
1
0
-1
-2
1,00
0,80
0,60
0,40
0,20
0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI


R=0.16
3
2
1
0
-1
-2
0,30
0,40
0,50
0,60
0,70
0,80
0,90
NDVI


(a)
Tocantins
Precipitation
3 2 1 0 -1 -2 -3
0,80 0,70 0,60 0,50 0,40 0,30 0,20 0,10 0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI


R=0.34
3 2 1 0 -1 -2 -3
0,20 0,30 0,40 0,50 0,60 0,70 0,80
NDVI


(b)
Pará
Precipitation
3 2 1 0 -1 -2
0,80 0,60 0,40 0,20 0,00
1985 1989 1990 1991 1994 1995 1999 2000 2001 2002 2003 2005 2007 2011 2012 2015
Average four month precipitation
NDVI


R=0.45
3 2 1 0 -1 -2
0,10 0,20 0,30 0,40 0,50 0,60 0,70 0,80
NDVI

Appendix C - Summary of the results of the regression statistic for the states of figure 17 and Appendix B (a) Rio Grande do Sul (b) Roraima (c) Santa Catarina (d) São Paulo (e) Paraná (f) Minas Gerais (g) Goiás (h) Distrito Federal (i) Mato Grosso do Sul (j) Mato Grosso (l) Bahia (m) Piauí (n) Maranhão (o) Tocantins (p) Pará.

(a)

Summary of results (RIO GRANDE DO SUL)

Regression Statistics	
Multiple R	0,611271
R Square	0,373652
Adjusted R Square	0,328913
Standard Error	0,056733
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,695101	0,018175	38,2447	1,45E-15	0,656119	0,734083
seansonal_mean	0,091077	0,031515	2,88994	0,011876	0,023484	0,15867

(b)

Summary of results (RORAIMA)

Regression Statistics	
Multiple R	0,392163
R Square	0,153792
Adjusted R Square	0,093348
Standard Error	0,058098
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,800382	0,014531	55,08202	9,05E-18	0,769217	0,831548
seansonal_mean	0,025913	0,016245	1,595114	0,133006	-0,00893	0,060756

(c)

Summary of results (SANTA CATARINA)

Regression Statistics	
Multiple R	0,150949
R Square	0,022785
Adjusted R Square	-0,04702
Standard Error	0,032108
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,73213	0,008028	91,20236	7,93E-21	0,714912	0,749347
seansonal_mean	0,005171	0,00905	0,571345	0,576824	-0,01424	0,024581

(d)

Summary of results (SÃO PAULO)

Regression Statistics	
Multiple R	0,477142
R Square	0,227664
Adjusted R Square	0,172498
Standard Error	0,065918
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,73213	0,008028	91,20236	7,93E-21	0,607447	0,683142
seansonal_mean	0,005171	0,00905	0,571345	0,576824	-0,084	0,002279

(e)

Summary of results (PARANÁ)

Regression Statistics	
Multiple R	0,22243
R Square	0,049475
Adjusted R Square	-0,018419
Standard Error	0,170348
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,714716	0,050876	14,04832	1,21E-09	0,605599	0,823833
seansonal_mean	0,126717	0,148443	0,853642	0,407672	-0,19166	0,445095

(f)

Summary of results (MINAS GERAIS)

Regression Statistics	
Multiple R	0,177142
R Square	0,031379
Adjusted R Square	-0,03781
Standard Error	0,070443
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,607386	0,017928	33,87927	7,77E-15	0,568934	0,645838
seansonal_mean	-0,01239	0,018397	-0,67345	0,511624	-0,05185	0,027068

(g)

Summary of results (GOIÁS)

Regression Statistics	
Multiple R	0,412561
R Square	0,170207
Adjusted R Square	0,110936
Standard Error	0,079729
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,647061	0,020032	32,30189	1,5E-14	0,604098	0,690025
seansonal_mean	0,031775	0,018751	1,6946	0,11227	-0,00844	0,071992

(h)

Summary of results (DISTRITO FEDERAL)

Regression Statistics	
Multiple R	0,125149
R Square	0,015662
Adjusted R Square	-0,05465
Standard Error	0,082987
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,616859	0,020868	29,56056	5,11E-14	0,572102	0,661616
seansonal_mean	0,013777	0,029191	0,471975	0,644216	-0,04883	0,076385

(i)

Summary of results (MATO GROSSO DO SUL)

Regression Statistics	
Multiple R	0,343699
R Square	0,118129
Adjusted R Square	0,055138
Standard Error	0,068044
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,699355	0,023531	29,72096	4,75E-14	0,648886	0,749823
seansonal_mean	0,023717	0,017319	1,369431	0,192432	-0,01343	0,060861

(j)

Summary of results (MATO GROSSO)

Regression Statistics	
Multiple R	0,257973
R Square	0,06655
Adjusted R Square	-0,00013
Standard Error	0,117926
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,653663	0,029512	22,14875	2,68E-12	0,590365	0,716961
seansonal_mean	0,033365	0,033396	0,999062	0,33472	-0,03826	0,104992

(l)

Summary of results (BAHIA)

Regression Statistics	
Multiple R	0,257973
R Square	0,06655
Adjusted R Square	-0,00013
Standard Error	0,117926
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,257973	0,257973	0,257973	0,257973	0,257973	0,257973
seansonal_mean	0,06655	0,06655	0,06655	0,06655	0,06655	0,06655

(m)

Summary of results (PIAUÍ)

Regression Statistics	
Multiple R	0,0165
R Square	4,15E-05
Adjusted R Square	-0,07138
Standard Error	0,074584
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,628549	0,018834	33,37385	9,57E-15	0,588155	0,668943
seansonal_mean	0,000664	0,027551	0,024099	0,981114	-0,05843	0,059755

(n)

Summary of results (MARANHÃO)

Regression Statistics	
Multiple R	0,16561
R Square	0,027427
Adjusted R Square	-0,04204
Standard Error	0,133823
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,613637	0,034703	17,68252	5,67E-11	0,539206	0,688067
seansonal_mean	-0,02102	0,033451	-0,62833	0,539902	-0,09276	0,050726

(o)

Summary of results (TOCANTINS)

Regression Statistics	
Multiple R	0,345235
R Square	0,119187
Adjusted R Square	0,056272
Standard Error	0,113877
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,569626	0,028616	19,90566	1,15E-11	0,50825	0,631002
seansonal_mean	0,034479	0,025051	1,376374	0,190322	-0,01925	0,088208

(p)
Summary of results (PARÁ)

Regression Statistics	
Multiple R	0,454365
R Square	0,206448
Adjusted R Square	0,149765
Standard Error	0,095524
Observation	16

	Coefficients	*Standard Error*	*t Stat*	*p- value*	*lower 95,0%*	*upper95,0%*
Intercept	0,512659	0,024782	20,6864	6,8E-12	0,459506	0,565812
seansonal_mean	0,048735	0,025536	1,908453	0,077051	-0,00604	0,103505
