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Possibilities for Using Google Engine Earth (GEE) Tools in Climate and Environmental Studies in the Northeast Region of Brazil: Studies with SPI, SPEI and NDVI

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A B S T R A C T

The study presents an assessment of the possibilities for using the digital tools contained in Google Earth Engine (GEE) for application in climate and environmental studies in the regions contained in the Northeast region of Brazil (NEB), in particular the use of tools that enable the calculation of Standardized Precipitation Index (SPI) and Standardized Precipitation and Evapotranspiration Index (SPEI) and the Normalized Difference Vegetation Index (NDVI) in these regions. The motivation for this assessment is based on studies published in the literature that attest to the efficiency and relative practicality of using these indices to monitor drought periods and vegetation dynamics in various regions of the world. Thus, the indices were obtained for the period from 2000 to 2019, which coincides with the analyses of the regionalization of observed rainfall and allowed the division of the NEB into seven homogeneous regions. The results obtained show significant patterns of variation in moisture conditions and vegetation density in the regions under study, highlighting periods of drought that are crucial for water resource management in the NEB. Thus, it is concluded that this free and accessible tool allows for climate studies that can assist in the environmental monitoring of these regions, in agreement with studies published in the literature for other regions of the country and the world.

Keywords: Precipitation indices; vegetation index; Northeast Brazil.

Possibilidades de Utilização das Ferramentas Google Engine Earth (GEE) em Estudos Climáticos e Ambientais na Região Nordeste do Brasil: Estudos com SPI, SPEI e NDVI

R E S U M O

O estudo apresenta a avaliação das possibilidades do uso das ferramentas digitais contidas no Google Engine Earth (GEE) para aplicação em estudos climáticos e ambientais nas regiões contidas na região Nordeste do Brasil (NEB), em particular o uso das ferramentas que possibilitam o cálculo dos índices de Precipitação Padronizada (SPI) e Padronizado de Precipitação e Evapotranspiração (SPEI) e do o Índice de Vegetação por Diferença Normalizada (IVDN) nessas regiões. A motivação para a realização desta avaliação baseia-se em estudos publicados na literatura que atestam a eficiência e a relativa praticidade do uso destes índices para o monitoramento dos períodos de secas e da dinâmica da vegetação em diversas regiões do mundo. Dessa forma, os índices foram obtidos para o período de 2000 a 2019, período que coincide com as análises da regionalização das chuvas observadas e que permitiu obter a divisão do NEB em sete regiões homogêneas. Os resultados obtidos mostram padrões significativos de variação nas condições de umidade e da densidade da vegetação nas regiões em estudo, destacando períodos de seca que são cruciais para a gestão dos recursos hídricos no NEB. Assim, conclui-se que esta ferramenta de acesso e gratuito permite a realização de estudos climáticos e que podem auxiliar no monitoramento ambiental dessas regiões, concordando-se com os estudos publicados na literatura para outras regiões do país e do mundo.

Palavras-chave: Índices de Precipitação; índice de Vegetação; Nordeste do Brasil.

Introdução

Climate and environmental studies in the Northeast Region of Brazil (NEB) are of great importance for understanding the dynamics and impacts that climate variability can have on the various biomes existing in the different subregions contained within the NEB. These studies can determine investments in production and preservation projects in areas of economic and environmental interest in these regions (Sousa et al., 2024).

Particularly in the Semi-Arid Region of the NEB (RSANEB), there are regions of economic interest dedicated to food production through agriculture and livestock, as well as areas of environmental protection, renewable energy production, and environmental tourism (Ribeiro et al., 2024; Silva and Gonçalves, 2024).

Thus, it is important to mention that these studies require meteorological and environmental data sets obtained through conventional and/or automatic data collection stations, which requires high financial investments for the installation and maintenance of measuring equipment and for making this data available on a public access network.

It is mentioned that an alternative technology for obtaining these climate and environmental data sets is available on the Google Earth Engine (GEE) platform, which enables cloud-based geospatial processing (Google Cloud) and provides analyses of various geospatial data sources that can be accessed by a personal computer with internet access (Gorelick et al., 2017).

GEE provides publicly downloadable Earth system observation data, as well as advanced algorithms for analysis in an interactive environment and long time series with observation records that may be important for environmental monitoring and analysis, thus making it a computational tool with potential applications for the development of climate and environmental studies and products for sectors of economic interest in various regions of the world (Amani et al., 2020; Zhao et al., 2021).

A dataset that combines information from satellite images with observations from weather stations to obtain the total rainfall in a given region, thus enabling diagnoses and the development of forecasting routines that can assist in studies and planning of government actions for adaptation, mitigation, and coexistence with the effects of climate variability and change in a given region (Singh et al., 2022; Arab and Ahamed, 2023).

Several other studies found in the literature agree that this technological tool provides useful information at low operational cost that can assist in climatological and environmental studies, as well as in the planning and development of mitigation, adaptation, and coexistence actions and strategies, with the observed climate variability and natural disasters that stand out in semi-arid regions, such as those found in RSANEB (Carvalho et al., 2016; Medeiros-Feitosa and Oliveira, 2020; Almeida et al., 2024).

There are several other studies in the literature that use this platform as an alternative for obtaining data sets for conducting complex studies and analyses in a collaborative manner for the development of environmental public policies in various regions of the world (Gorelick et al., 2017; Ali et al., 2022; Freire-Silva et al., 2022).

In addition, it should be noted that all these authors validated the total annual precipitation estimates obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), demonstrating the possibility of using this dataset for these types of studies and to assist in the development of public policies in the various regions contained in the NEB.

In this context, the objective of this study is to show some possibilities for using GEE that can assist in the development of climate and environmental studies in regions of the NEB, such as the calculation of the Standardized Precipitation Index (SPI), the Standardized Precipitation and Evapotranspiration Index (SPEI), and the Normalized Difference Vegetation Index (NDVI).

The Standardized Precipitation Index (SPI) is a metric used to quantify drought, which associates a numerical value with precipitation and indicates deviations from this value in relation to the historical average of this variable. The SPI allows for comparison between regions and periods of the year, as it can be calculated on different time scales (monthly or annually). Negative values indicate a lack of rain (droughts) and positive values indicate excess rain, with zero representing the climatological average (Gois et al., 2024).

The SPEI index allows the severity of drought in a given region over a given time interval to be determined and classified. It is an update of the Standardized Precipitation Index (SPI) recommended by the World Meteorological Organization (WMO) (Santos et al., 2019).

The NDVI index is a sensitive indicator of the quantity and condition of vegetation obtained by remote sensing and represents a technological process that allows the collection and representation of data from a region without the need for direct contact, i.e., the information is collected remotely (Gomes et al., 2023).

Possibilities for using indices (SPI, SPEI, and NDVI) in climate and environmental studies.

The following are studies published in the literature that show the application of indices (SPI, SPEI, and NDVI) in climate studies with observed precipitation data from various regions of the world, including Brazilian regions.

Regarding studies that used the Standardized Precipitation Index (SPI) in climate studies. Silva et al. (2021) evaluated the spatiotemporal variability of this index with the aim of identifying periods of water scarcity and excess in the Choró River Basin in the state of Ceará. Thus, the authors state that the SPI proved useful for quantifying dry and rainy events in this region on short-medium, and long-term time scales.

Almeida et al. (2023) evaluated the dominant spatial patterns of this index with the aim of identifying homogeneous regions of precipitation regime in the state of São Paulo. They concluded that this type of study is important for understanding how extreme precipitation events occur in this region and are distributed spatially and temporally, and to assist in monitoring this variable.

Lopes et al. (2024) used the SPI index to analyze the occurrence of extreme precipitation events in Manaus, Amazonas, between 2002 and 2023. The authors mention the importance of this index as a tool for water resource planning and climate adaptation strategies, emphasizing the need for future studies integrating new indicators and climate models for a more comprehensive understanding of local climate dynamics.

Gois et al. (2024) investigated the occurrence of droughts in the state of Acre by calculating the SPI on a twelve-month scale and its association with the variability of the ONI (Oceanic Niño Index) associated with the occurrence of the ENSO (El Niño – Southern Oscillation) phenomenon. This once again attests to the importance of using this index in climate studies.

Barros et al. (2021) conducted a study using the SPI and the Mann-Kendall test at a 5% significance level to assess the variability trends of this index at different time scales, from one to forty-eight months, with precipitation data obtained from a weather station located in the city of Recife in the state of Pernambuco.

Studies published using SPEI

Tong et al. (2018) mention that knowledge about climate variability, particularly about the patterns of occurrence of drought periods, known as dry periods, is fundamental for planning water resource management in a given region. Thus, they used the Standardized Precipitation Evapotranspiration Index (SPEI) to investigate and develop a methodology to predict these drought patterns in regions of Mongolia.

In addition, Pei et al. (2020) state that global warming has increased the frequency of dry periods in the Mongolia region, and that it is therefore of utmost importance to select and choose an appropriate index to monitor this climate variability in these regions. Furthermore, the authors indicate that one such index is the standardized precipitation evapotranspiration index (SPEI), as it considers the influence of air temperature in its mathematical formulation.

Wang et al. (2021) agree with the authors cited above, mentioning that the standardized precipitation evapotranspiration index (SPEI) can be used to monitor and evaluate the characteristics of drought periods at different time scales. They investigated the application of this index in regions of China to investigate the occurrence of meteorological, agricultural, and hydrological droughts, which cause socioeconomic damage in these regions.

Xia et al. (2024) also agree with the authors cited above, but mention that two problems with existing SPEI datasets are spatial discontinuity and inadequate spatial resolution, which limit the application of this method for drought monitoring in some regions of the planet.

Published studies using the NDVI

Below are some of the possible uses of NDVI in climate and environmental studies in certain regions of the planet. The authors mention that the Normalized Difference Vegetation Index (NDVI) is one of the first analytical products derived from satellite images that enable climate and environmental analyses, particularly for assessing vegetation dynamics in regions of environmental and economic interest (Huang et al., 2021; Pei et al., 2021).

In addition, the authors state that the popularity of this index is due to the ease of installing multispectral sensors on satellites, aircraft, and unmanned aerial systems, which detect images in the visible frequency range and another in the near-infrared range.

Al-Quraishi et al. (2021) confirm the authors' statements and investigated the frequency of drought periods and analyzed changes in vegetation cover in Iraqi regions using the NDVI obtained from satellite images from the Landsat collection.

Matinez and Labib (2023) state that the normalized difference vegetation index (NDVI) is used in most environmental studies published in specialized journals. In addition, they mention that this index makes it possible to measure more than just the proportion of green cover in regions. Thus, they cite that the NDVI also makes it possible to measure vegetation types and the relationship between changes in the quantity and types of vegetation, parameters that can assist in planning the development of actions aimed at monitoring vegetation in rural and urban areas.

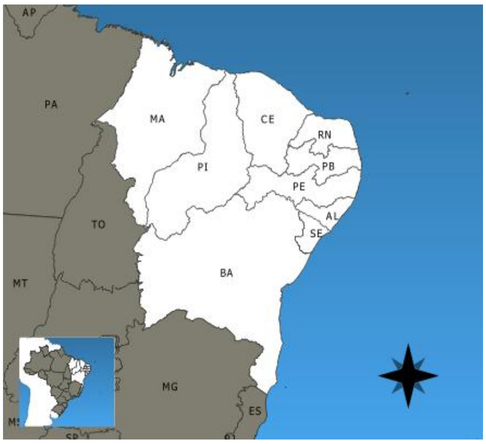
Birolo et al. (2024) also confirm the statements made by the authors cited above. The authors used the IVDN to identify the occurrence of heat islands in the municipality of Itapema/SC in Brazil. In this way, they were able to identify the correlation between the values obtained from the NDVI and the surface temperature in rural areas, in Permanent Preservation Areas (APP), and in urban areas of this municipality, which are associated with areas with and without vegetation cover and areas where urban buildings are concentrated, respectively.

In addition, the authors mention that studies of this nature are accessible to public managers and allow them to diagnose and understand the effects of changes in land cover in a given area or region. They also enable the planning of actions to monitor and mitigate the impacts of urban heat island formation in communities.

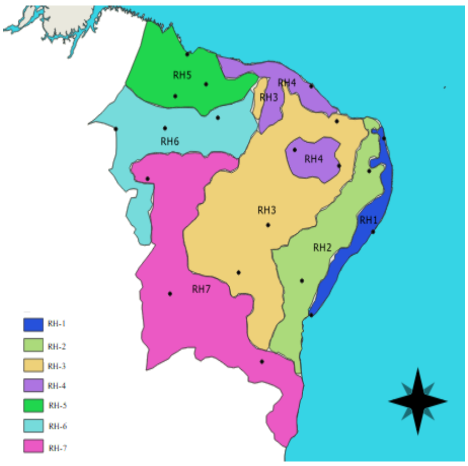
Thus, it is important to mention that the motivation for the development of this study, which investigates the possibilities of applying the GEE to obtain and apply these indices in climate and environmental studies in the regions contained in the NEB, is based on citations from studies published in the literature that use observed meteorological data. Thus, the use of GEE may represent the possibility of using these indices in regions that do not have these observed data, enabling a series of climate and environmental studies in these regions.

Materials and methods

In this study, the NEB will be divided into seven homogeneous rainfall regions, as used in the study by Almeida et al. (2024) (Figure 1), which were obtained from data from 244 weather stations distributed across the nine states in this region.



(a)



(b)

Figure 1. (a) Location of the NEB and (b) Homogeneous rainfall regions. Adapted from Costa (2020) by Almeida et al., (2024).

According to these authors, a hierarchical classification method was used to determine the homogeneous regions, based on the Euclidean distance metric and the sum of squares of deviations aggregation criterion. Thus, the number of homogeneous regions was obtained through cross-sections in the dendrogram based on the mathematical criterion of inertia and prior knowledge of the rainfall regime in the NEB.

Standardized Precipitation Index (SPI)

The SPI measures how many standard deviations the observed precipitation (in a given period) deviates from the climatic average, using a normal distribution after data transformation. It can be calculated for periods ranging from one to thirty-six months, allowing for the analysis of everything from short-term meteorological droughts to impacts on aquifers and reservoirs.

The values and classification of this index are found in Table 1.

Table 1 – SPI classification.

Index classification	SPI
Extremely wet	> 2,0
Very wet	1,50 a 1,99
Moderately wet	1,00 a 1,49
Normal	-0,99 a 0,99
Moderately dry	-1,49 a -1,00
Severely dry	-1,50 a -1,99
Extremely dry	< -2,00

Standardized Precipitation Evapotranspiration Index (SPEI)

One of the alternatives for calculating SPEI and conducting detailed climate studies is the digital tool based on Google Earth Engine (GEE) information and communication technology, which provides access to the SPEIbase information package. This allows for the efficient processing of large volumes of geospatial data, thus offering the possibility of understanding moisture conditions in a given region.

SPEI allows the severity of drought in a given region and time interval to be determined and classified. Thus, in this study, the SPEIbase v.2.8 package will be used to calculate the SPEI, which offers robust, long-term information on moisture conditions on a global scale and has a spatial resolution of 0.5° and a temporal resolution that allows for studies on time scales between 1 and 48 months for the SPEI (Santos et al., 2019).

Drought values can be classified Drought values can be classified according to Table 2 (Vicente-Serrano et al., 2010). Thus, the results obtained in this study will be analyzed based on the temporal scale (annual) – 12 months, classifying each year of the study period.

Thus, a case study was conducted for a period of 30 years of data (1990 to 2020), coinciding with the period used to determine homogeneous rainfall regions, in which SPEI analysis can assist in the development of effective water resource management strategies in the region under study.

Table 2 – SPEI classification.

Index classification	SPEI
No drought	SPEI ≥ - 0,5
Mild drought	-1 < SPEI < -0,5
Moderate drought	-1 < SPEI < -1,5
Severe drought	-1,5 < SPEI < -2
Extreme drought	SPEI ≤ -2,0

Normalized Difference Vegetation Index (NDVI)

Among the vegetation indices used to monitor vegetation cover variability and ecosystem vulnerability in the NEB region, the Normalized Difference Vegetation Index (NDVI) stands out, whose effectiveness is described in several studies published in the literature (Gameiro et al., 2016; Gomes et al., 2023).

The use of information and communication technology to calculate this index is a possibility that maximizes the computational cost of environmental studies. thus, it is mentioned that the Google Earth Engine (GEE) digital platform facilitates the processing of large volumes of data involved in the calculation of this index, which is fundamental for climate and environmental studies, including the calculation of the NDVI through images from the LandSat® collection (Nanki and Gilberto, 2018; Zhao et al., 2021).

The NDVI is a sensitive indicator of the quantity and condition of vegetation, whose values range from -1 to 1. Used in conjunction with remote sensing, it is a technological process that allows the collection and representation of data from a region without the need for direct contact, i.e., the information is collected remotely and defined by the following equation (Pettorelli et al., 2014).

$$NDVI = \frac{\rho_{NIR} - \rho_r}{\rho_{NIR} - \rho_r} \quad (1)$$

Em que: ρNIR é a refletância na faixa do infravermelho próximo e ρR é a refletância na faixa do vermelho.

The values and classification of this index are found in Table 3.

Table 3 – NDVI classification.

Index classification	IVDN
Water, snow, non-vegetated areas	< 0
Minimal vegetation – bare soil or rocks	0 a ~ 0,2
Sparse grass-like vegetation	~0,2 a ~0,4
Moderate vegetation or early crops	~0,4 a ~0,6
Dense vegetation – crops or forest	0,6 / até 1,0

Comparison of index characteristics

The following is a summary comparison of the characteristics of the indices described in this study that represent possibilities for use in climate studies in the regions contained in the NEB (Table 4).

Table 4 – Summary (SPI, SPEI e NDVI).

Index	Measurement	Scale (month)	Classification
SPI	Precipitation deviation from average	1 a 36	Table 1
SPEI	Precipitation – evapotranspiration	1 a 48	Table 2
IVDN	Vegetation – photosynthetic activity	–	Table 3

Statistical analysis of SPI calculations

A statistical analysis was performed using the coefficient of determination (R^2) to determine how much of the SPI variability calculated with the observed data is captured by the data series obtained from the CHIRPS dataset.

The R^2 coefficient is a statistical measure that indicates the capture of variability between two data sets, composed of a dependent variable and one or more independent variables, whose value generally varies between zero and one, or between 0 and 100%. Thus, in this case, the closer to one (or 100%), the greater the explanatory power of the CHIRPS data set.

It should be noted that the R^2 coefficient can be obtained by squaring the value of Pearson's statistical correlation coefficient, according to equation 2.

$$R^2 = r^2 \tag{2}$$

Pearson's coefficient (r) is a statistical measure that indicates the strength and direction of the linear relationship between two continuous numerical variables, as shown in the equation, whose value varies between –1 and +1.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \cdot \sum(y_i - \bar{y})^2}} \tag{3}$$

The classification of this coefficient (r) is shown in Table 5.

Table 5 – Pearson coefficient classification.

Classification	***r***
Very strong statistical correlation	$\|r\| \geq 0,9$
Strong statistical correlation	$0,7 \leq \|r\| < 0,9$
Moderate statistical correlation	$0,5 \leq \|r\| < 0,7$
Weak statistical correlation	$0,3 \leq \|r\| < 0,5$
Negligible statistical correlation	$\|r\| < 0,3$

Google Earth Engine (GEE)

Google Earth Engine (GEE) is a geospatial data processing and analysis platform developed by Google, designed to process large data sets. It provides access to a vast collection of satellite images and geospatial data from various sources, thus enabling advanced spatial analysis and modeling of terrestrial phenomena on a global scale (Funk et al., 2015; Rodrigues et al., 2019).

The platform offers a wide range of tools and algorithms for image processing, information extraction, and data visualization, making it a powerful tool for researchers, scientists, and professionals in various fields, including climatology, agriculture, environmental conservation, urban planning, among others.

Thus, it facilitates access to and analysis of geospatial data in a collaborative and interoperable manner, promoting significant advances in the understanding and monitoring of our planet.

Among these options is the CHIRPS Dataset, which has a spatial resolution of 0.05°, approximately 5 km near the equator, covering 50°S and 50°N, with data from 1981 to the present day. The CHIRPS precipitation estimate is composed of various sources of meteorological information from operational and research centers around the globe, including satellite data, numerical models, and various observations from weather stations (Funk et al., 2015; Rodrigues et al., 2019).

Results

The following are the results obtained from calculations of the indices (SPI, SPEI, and NDVI) using the GEE technological tool in the NEB regions.

Index Calculations

The results presented in this section compare the calculations of the Standardized Precipitation Index (SPI) on a twelve-month time scale, obtained from meteorological data from the National Institute of Meteorology (INMET) stations and from the estimated data contained in the CHIRPS Dataset for the various NEB regions, for the period from 1990 to 2019.

The Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS Dataset) is a near-global precipitation dataset spanning more than 30 years, which incorporates 0.05° resolution satellite imagery with in situ station data to create gridded precipitation time series for trend analysis and seasonal drought monitoring.

For RH-1, analyses showed that CHIRPS captures variations in the observed SPI, with correspondence between the datasets. However, discrepancies are observed in years of climatic extremes, indicating limitations or the need for adjustments. The R^2 coefficient of 0.53 demonstrates that there is a moderate statistical correlation between the data sets, explaining 53% of the observed variation, which points to a certain capacity of the data contained in CHIRPS to represent the variability of the SPI calculated with observed data (Figure 2).

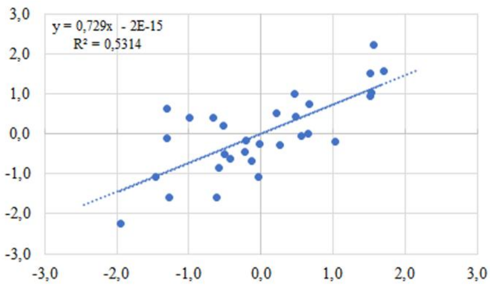


Figure 2. SPI values for RH-1.

In RH-2, calculations were performed for the period from 1994 to 2019. It can be observed that despite the accuracy (R2=0.73), there are discrepancies in several years, such as 1997 and 2001, in which the CHIRPS dataset tends to underestimate the SPI, suggesting that external factors or uncertainties in the data may affect unexplained variability (Figure 3).

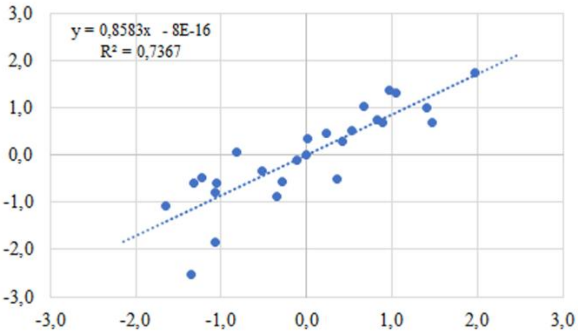


Figure 3. SPI values for RH-2.

For RH-3 (Figure 4), it was found that the SPI values calculated from CHIRPS data showed large discrepancies in relation to the values calculated from observed data. thus, an R^2 of 0.12 was obtained, confirming the low statistical correlation between these data sets, indicating that CHIRPS data are not suitable for use in climate studies in this region.

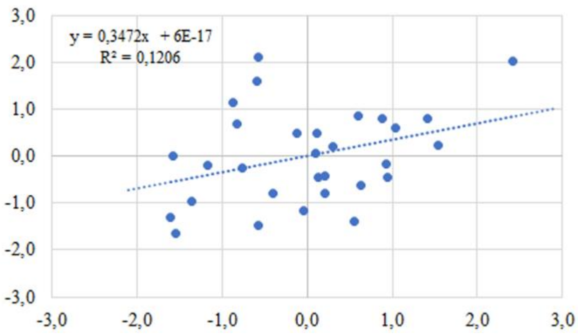


Figure 4. SPI values for RH-3.

In RH-4, the SPI values obtained through the CHIRPS Dataset for the period from 1994 to 2019 capture the trends of the SPI calculated with observed data, with R^2=0.64, despite presenting limitations in years of extreme events, such as 2008 and 2011 (Figure 5).

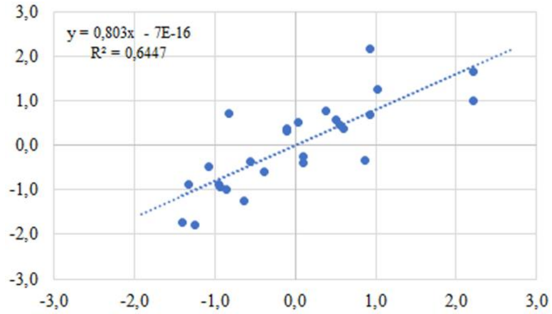


Figure 5. SPI values for RH-4.

The SPI values calculated in the RH-5 region using CHIRPS data show strong correspondence with the values calculated from observed data, especially after 2000. An R^2 of 0.89 was obtained, indicating a strong statistical correlation, as shown in Figure 6.

In RH-6, the R^2 calculated between the SPI values obtained through the CHIRPS Dataset and those obtained through the observed values was 0.61, indicating moderate statistical correlation (Figure 7).

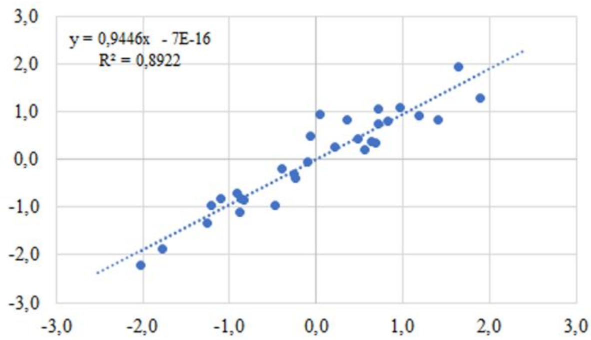


Figure 6. SPI values for RH-5.

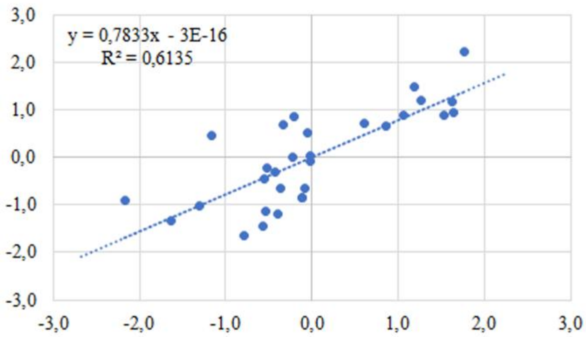


Figure 7. SPI values for RH-6.

For RH-7, the CHIRPS Dataset proved effective in reproducing the SPI values calculated using the observed data set, with an R2 of 0.68, confirming a good fit between the curves of the data series for this index.

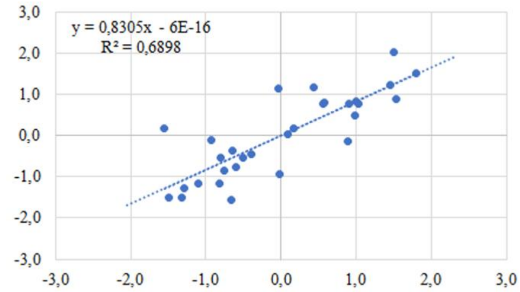


Figure 8. SPI values for RH-7.

SPEI Index

The results obtained for the calculation of the SPEI index in the regions under study are presented below. It should be noted that in this case, the results presented are calculations obtained directly from the GEE with access to the SPEIbase dataset.

Figure 9 shows that the SPEI shows significant variations in climatic conditions over the years in the period under study (1990 to 2019). The period between 1990 and 2011 saw RH-1 alternate between dry and wet periods, with 1998 and 1999 (SPEI of -0.89 and -0.87) showing a period of drought, i.e., rainfall below the climatological average. From 2012 to 2016, RH-1 saw a period of rainfall below the climatological average, represented by negative SPEI values, especially in 2013 (-0.86) and 2016 (-0.87).

Figure 10 shows the values for RH-2. This region showed a period of fluctuating humidity conditions (1990 to 2001), with positive and negative SPEI values, followed by a dry period (2002 to 2019), with 2013 (-0.90), 2016 (-0.87) and 2017 (-0.92) standing out. In this context, it should be noted that the results obtained show the urgent need to plan strategies for managing and living with drought in the region.

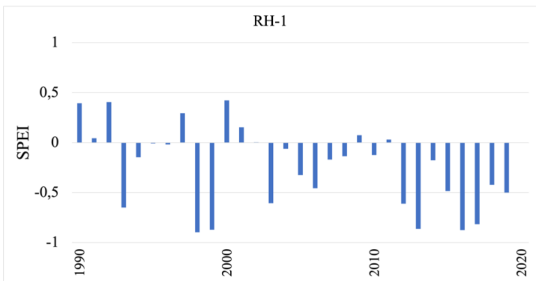


Figure 9. SPEI values for RH-1.

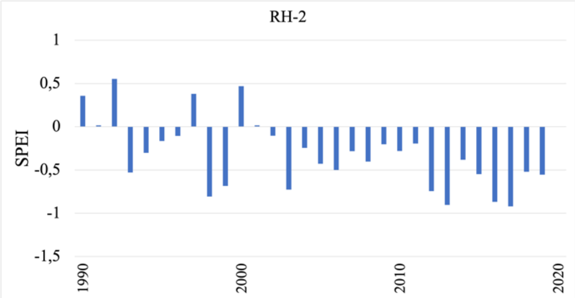


Figure 10. SPEI values for RH-2.

For the RH-3 homogeneous region (Figure 11), there was a period of significant fluctuations in humidity conditions from 1990 to 2001 and a period of below-average rainfall from 2002 onwards, with SPEI values indicating moderate drought in 2013 (-1.00) and mild drought in 2015 (-0.86) and 2016 (-0.96). These results, similar to the two previous ones, demonstrate the need for drought management and coping strategies for this region as well.

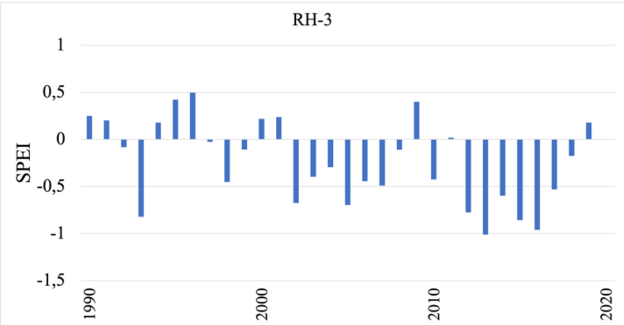


Figure 11. SPEI values for RH-3.

In RH-4 (Figure 12) there was a period of alternating humidity conditions over the years between 1990 and 2011, with SPEI values alternating between positive and negative, and from 2012 onwards there were dry years until 2019, with highlights being 2013 (-1.00), 2016 (0.86) and 2017 (0.86).

The values of this variable show that the RH-4 region is relatively humid, however, it faced a period with below-average rainfall (2012 to 2019) detected by the SPEI calculation, highlighting the importance of calculating this index for climatological studies in this region, agreeing with the results presented by Lima et al. (2019) for the sertão region of Rio Grande do Norte.

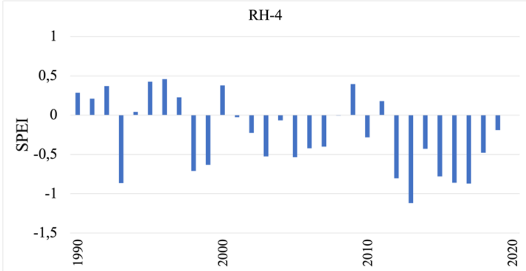


Figure 12. SPEI values for RH-4.

Figure 13 shows the SPEI values for RH-5. The results show similar patterns of variation in humidity conditions over the years, particularly in the period between 1990 and 2011, during which dry and wet years and periods alternate. And, similar to previous analyses, a dry period is observed between 2012 and 2019, with 2013 and 2016 also standing out, with SPEI values indicating severe drought.

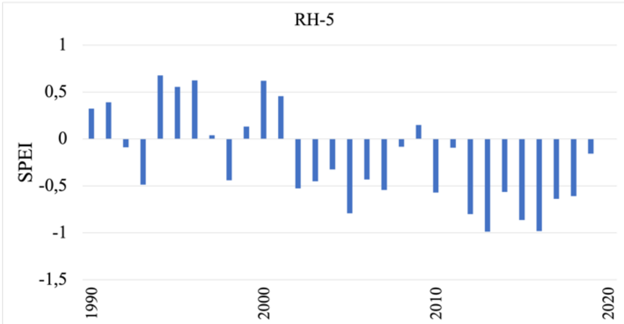


Figure 13. SPEI values for RH-5.

For the RH-6 region (Figure 14) there is also a period of alternation between dry and wet years, from 1990 to 2001, and an extensive period with negative SPEI values from 2002 to 2019, indicating an extensive period of years with rainfall below the climatological average in this region. The sub-period between 2012 and 2019 stands out, with SPEI values that indicate years classified as extremely dry, such as 2013 (-0.91), 2015 (-0.91) and 2016 (-1.00). It is worth mentioning that climatological studies are extremely necessary in this region to aid planning and indicate alternatives for living with drought.

The SPEI index values for the RH-7 region are shown in Figure 15. The results are similar to those obtained for the other regions analyzed in this study, showing a period (1990 to 2001) of alternating positive and negative SPEI values, which indicate wet and dry years, respectively. There is also a long dry period from 2002 to 2019, with 2016 and 2017 standing out as the driest years in the series, with SPEI values of -0.99, respectively.

The analysis of the SPEI for the homogeneous regions of the NEB in the period between 1990 and 2019 reveals significant patterns of variation in humidity conditions, highlighting periods of drought that are crucial for managing water resources in the region.

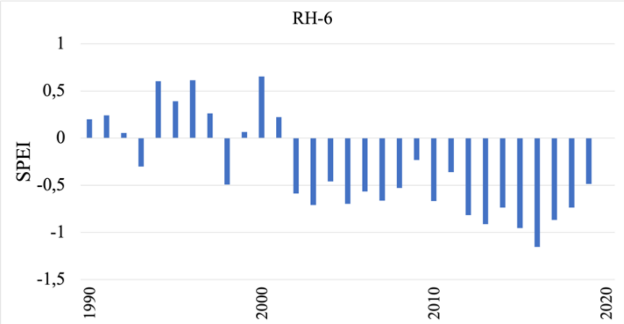


Figure 14. SPEI values for RH-6.

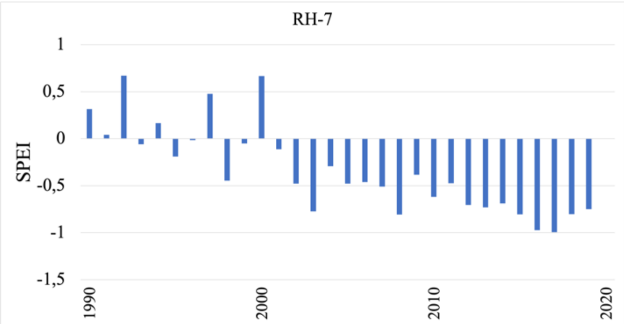


Figure 15. SPEI values for RH-7.

The use of the GEE platform in conjunction with the SPEIbase database proved to be an efficient tool for identifying and assessing the severity of droughts, corroborating the results of studies published in the literature (Santos et al., 2019; Sousa et al., 2024). The analyses indicate that most regions experienced prolonged periods of drought, with significant variations in the intensity and duration of these events over time.

In addition, the results obtained for the homogeneous rainfall regions of the NEB, in particular for the regions located in the states of Maranhão, Piauí and part of the state of Bahia (RH-5, RH-6 and RH-7), confirm the results published in the literature, which identified periods of drought between 2011 and 2019 in the MATOPIBA region (Sousa et al., 2024).

Thus, calculating the SPEI using the digital GEE tool in conjunction with the SPEIbase platform was fundamental to identifying these climate patterns, which show rainfall below the climatological average in this period. It should be noted that the calculation of this index can assist climatological studies in various regions of the NEB, particularly in regions of economic interest, such as MATOPIBA and Semi-arid region of the NEB.

NDVI Index

The NDVI index values for the RH-1 region (Figure 16) in the period from 1990 to 2019 vary between 0.12 and 0.27, with an average of the values obtained in the period over the years of approximately 0.18.

These variations reflect changes in the density and health of vegetation in the region, which can be influenced by factors such as climate variability and change, extreme events (such as droughts and floods) and the agricultural practices adopted in this region. In addition, it should be noted that since 2011 there has been an increase in the values obtained, which suggests recovery or better management of the vegetation in this region.

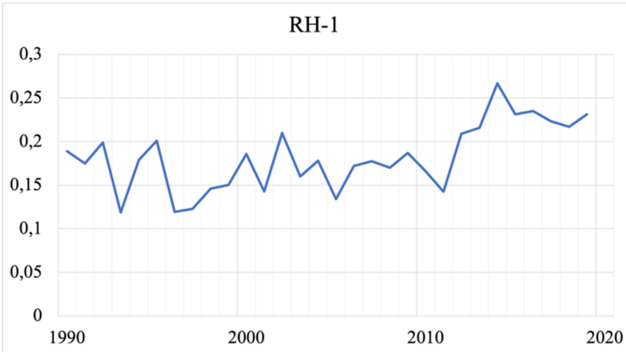


Figure 16. NDVI values for RH-1.

In the RH-2 region, the NDVI ranged from 0.21 in 1990 to 0.24 in 2019 (Figure 17). The values indicate a trend of moderate growth in vegetation over time, with a positive response to environmental conditions and the management practices implemented in the region. The lowest values in 1998 (0.14) indicate periods of stress for the vegetation, while the peaks in 2000 and 2010 (0.22 and 0.25) suggest years of favorable climatic conditions and potentially improvements in agricultural practices in the region.

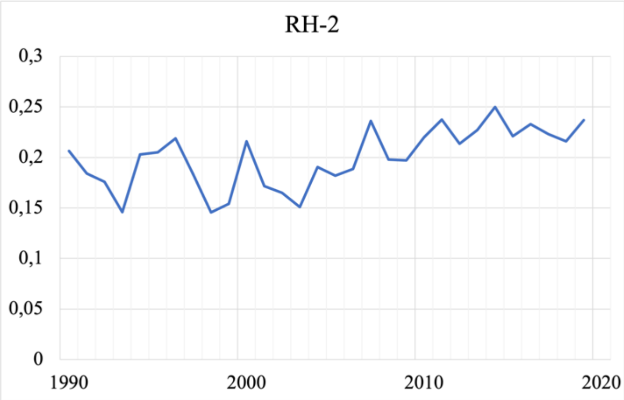


Figure 17. NDVI values for RH-2.

Figure 18 shows the NDVI values for RH-3, which vary from 0.17 in 1993 to 0.28 in 2019, demonstrating a general upward trend in vegetative density over the decades analyzed. The lower values, such as that obtained for 1993, may indicate the influence of unfavorable climatic conditions or inadequate agricultural management practices, while the peaks in 2002 and 2011 (0.32 and 0.28) reflect periods of favorable environmental conditions and perhaps investments in more sustainable agricultural practices in the region.

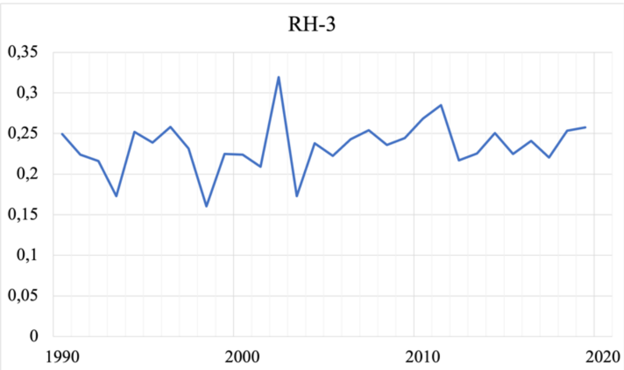


Figure 18. NDVI values for RH-3.

Figure 12 shows the variation in NDVI values for RH-4. A value of 0.24 can be seen in 1990 and a peak of 0.26 in 2018. The RH4 region shows a positive response to environmental conditions and the management practices implemented. The lower values in 1998 (0.14) may indicate periods of stress for the vegetation, while the peaks in 2002 and 2018 (0.315 and 0.257, respectively) suggest years of favorable climatic conditions and effective management practices.

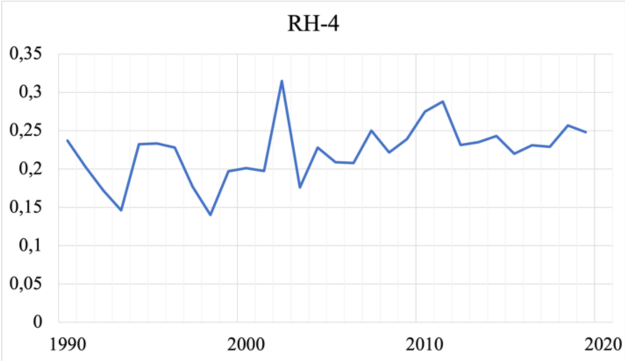


Figure 12. SPEI values RH-4.

In the RH-5 region (Figure 13), the NDVI varied from 0.30 in 1995 to 0.43 in 2019, indicating an upward trend in vegetative density over the decades analyzed. The lower values in 1990 (0.30) may reflect unfavorable climatic conditions or inadequate management practices, however, the values presented in 1994 and 2019 (0.48 and 0.43) indicate periods of possible investment in more sustainable agricultural practices. This region demonstrates a robust response to environmental conditions, with consistently high values that suggest effective management practices and an environment conducive to plant growth.

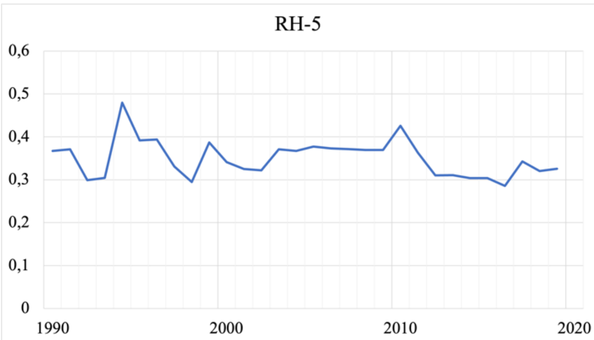


Figure 13. NDVI values RH-5.

Figure 14 shows the NDVI values obtained for the RH-6 region. It can be seen that the values ranged from 0.29 in 2016 to 0.38 in 2014, which shows a trend towards an increase in vegetative density during the study period.

The increase can be explained by improvements in environmental conditions and management practices that promote an environment conducive to plant growth. The lower values in 2016 may have been influenced by unfavorable weather conditions or inadequate management practices, while the peaks in 2014 indicate periods of favorable environmental conditions and perhaps investments in more sustainable agricultural practices.

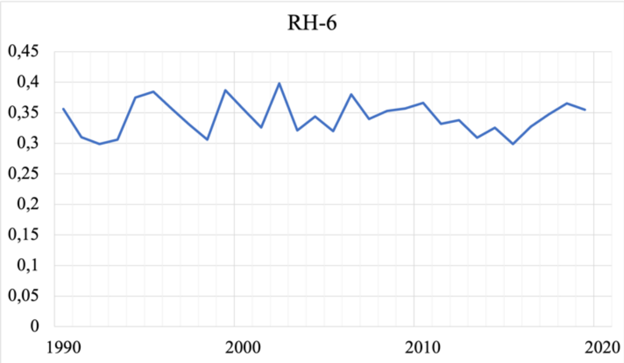


Figure 14. SPEI values for RH-6.

In the RH-7 region (Figure 15) there is a variation in NDVI values over time that represents a general increase in vegetative density. In 1990, the NDVI showed a value of 0.298 and reaching a peak of 0.355 in 2019, the RH-7 region demonstrates a positive response to environmental conditions and the management practices implemented.

However, in 1998 the lowest NDVI value of 0.269 may indicate periods of stress for the vegetation, while the peaks in 2002 and 2019 (0.376 and 0.355, respectively) suggest years of favorable climatic conditions and effective management practices.

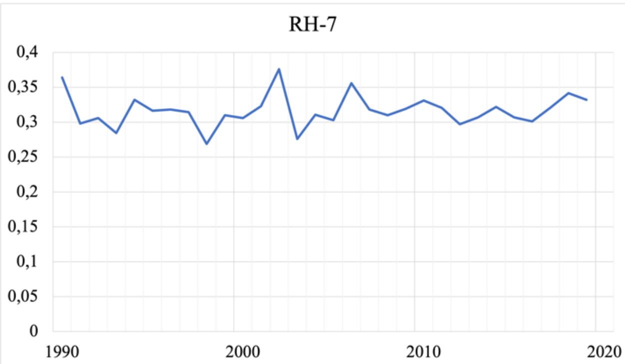


Figure 15. NDVI values for RH-7.

The results obtained and presented in this study show that the calculation of the NDVI for all the homogeneous rainfall regions in the NEB region indicate distinct trends of variation in vegetation density over the period investigated. These results corroborate those published in the literature (Santos et al., 2019; Sousa et al., 2024). Thus, it is found that this index calculated by this and other methodologies for the semi-arid region of the NEB shows lower values compared to other regions, such as the southern coastal region of the state of Bahia and the regions of the states of Maranhão and Piauí.

It should be noted that the variations in vegetation density in the study area over the period investigated are directly influenced by a combination of environmental, climatic and anthropogenic factors. In this period, the occurrence of climatic meteorological phenomena such as El Niño and La Niña stand out, which directly influence the amount of rainfall observed in the region and which in turn influence the dynamics of vegetation in the NEB.

In this context, it is also mentioned that the calculation of the NDVI using the methodology proposed in this study can assist both in climatological studies and in the continuous monitoring of environmental variability observed in the various regions of the NEB.

Conclusions

The case study on the variability of the Standardized Precipitation Index (SPI) calculated using observed data and the CHIRPS Dataset in regions of Northeast Brazil (NEB) yielded promising results. Thus, satisfactory performance was found in some regions, with high R2 values that show the ability of this dataset to represent the observed SPI variability in these regions.

In this case, it should be noted that the methodology used in this case study presented a limitation in RH-3, where performance was classified as low, with a low R2 value, indicating difficulty in predicting fluctuations and extreme events in these regions.

In this context, it is concluded that the CHIRPS Dataset is a promising tool for calculating the SPI in NEB regions and for climate monitoring in these regions, particularly in regions where climate data does not exist or is unreliable.

The results obtained in the second case study showed that calculating the SPEI using this low-computational-cost processing methodology can assist in monitoring and understanding climate variability in the regions under study, especially the variability associated with the occurrence of climatological drought periods, thus enabling assistance in planning management, adaptation, and mitigation strategies for the effects caused by these dry periods that are frequently observed in the NEB regions.

This reinforces the statements found in the literature that GEE is a free and easily accessible digital tool that allows, through various data acquisition and analysis tools, the performance of climate studies in different regions and spatial and temporal scales.

The study also demonstrated the possibility of calculating the NDVI for the regions contained in the NEB region using this digital platform, which uses information and communication technology to provide a set of satellite images from the Landsat® collection that can be obtained, processed, and analyzed, allowing the identification of patterns of vegetation variation in the different homogeneous rainfall regions used in this study.

Thus, it can be concluded that, based on the analysis of this index using this methodology, it is possible to diagnose variations in plant density and vegetative health, thereby contributing to environmental monitoring and the planning of agricultural management practices that promote the recovery and preservation of vegetation cover in these regions.

Finally, it should be noted that, in agreement with the studies published in the literature cited in this study, the integration of methodologies that use remote sensing techniques for climate and environmental acquisition and analysis, such as the tools available in GEE, with sustainable agricultural management practices can contribute to the monitoring and planning of actions that promote the resilience of the various biomes and ecosystems found in the NEB regions.

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