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Response of semi-arid vegetation to agricultural drought determined by indices derived from MODIS satellite[1]

Resposta da vegetação semiárida à seca agrícola determinada por índices derivados do satélite MODIS

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HIGHLIGHTS:
The study provides a reference for evaluation and selection of indices for monitoring droughts in Paraíba state.
Vegetation health index (VHI) allows drought observations in high spatial and temporal resolution.
Using drought indices allows effective, innovative and efficient drought management.

ABSTRACT: Indices based on data from remote sensors play an important role in the characterization, mapping and monitoring of a drought event. Thus, the objective of this study was to monitor the dynamics of agricultural drought, through the response of vegetation, in the semi-arid region that comprises the state of Paraíba, Brazil, through MODIS satellite products applied to the VCI (vegetation condition index), TCI (temperature condition index) and VHI (vegetation health index) indices, and to evaluate the correspondence of VHI index with standardized precipitation index (SPI) and agricultural standardized precipitation index (aSPI). In this study, values of NDVI (normalized difference vegetation index) and LST (land surface temperature) - covering the period between 2010 and 2020 - were used to estimate VCI, TCI and VHI. In addition, the correspondence of VHI with SPI and aSPI was evaluated at the 12-month time scale, conducted using Pearson's correlation analysis. Characteristics of a stressed vegetation predominated in the study region, due to irregularity of precipitation and high temperatures, confirming the possibility of detection of droughts through VHI, VCI and TCI, and that the indices detected remotely and through local data are strongly correlated in drought detection.

Key words: vegetation health index (VHI), vegetation condition index (VCI), thermal condition index (TCI), drought indexes, NDVI

RESUMO: Os índices baseados em dados de sensores remotos desempenham um papel importante na caracterização, mapeamento e monitoramento de uma seca. Com isso, o objetivo deste estudo foi monitorar a dinâmica da seca agrícola, por meio da resposta da vegetação, na região semiárida que compreende o estado da Paraíba, Brasil, por meio de produtos de satélite MODIS aplicados ao VCI (índice de condição da vegetação), TCI (índice de condição térmica) e VHI (índice de saúde da vegetação). E também, avaliar a correspondência do índice VHI com o índice de precipitação padronizada (SPI) e o índice de precipitação padronizada agrícola (aSPI). Neste trabalho, as climatologias de NDVI (índice de vegetação por diferença normalizada) e LST (temperatura da superfície terrestre) - abrangendo o período entre 2010 e 2020 - foram usadas para estimar VCI, TCI e VHI. Além disso, foi avaliado a correspondência do VHI e o índice padronizado de precipitação (SPI) e índice agrícola de precipitação (aSPI), na escala de tempo de 12 meses, conduzidas usando a análise de correlação de Pearson. Na região de estudo predominaram características de uma vegetação estressada, devido à irregularidade de precipitação e altas temperaturas. Confirmando a possibilidade da detecção das secas através do VHI, VCI e TCI. E que os índices detectados remotamente e através de dados locais estão fortemente correlacionados na detecção de seca.

Palavras-chave: índice de saúde da vegetação (VHI), índice de condição da vegetação (VCI), índice de condição térmica (TCI), índices de seca, NDVI

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Introduction

Drought is a complex natural phenomenon that frequently affects the state of Paraíba, Brazil, which has a predominantly semi-arid climate (Brasil Neto et al., 2021). Currently, there are a number of indices that characterize and provide accurate information about the attributes and impacts of droughts (Svoboda & Fuchs, 2016).

Studies evaluating the applicability of drought indices are decisive to monitor, understand the size and manage the incidence of droughts in semi-arid regions. The magnitude and impact of drought on vegetation can be obtained by combining satellite data derived from moisture and thermal stresses present in the vegetation condition index (VCI) and thermal condition index (TCI), which combined generate the Vegetation Health Index (VHI). Such indicators are useful and improve the accuracy of drought classification (Kukunuri et al., 2020).

Indices based on meteorological data are frequently used in the analysis of droughts and have already been applied in semi-arid regions of northeastern Brazil (Brito et al., 2018; Souza et al., 2021).

The standardized precipitation index (SPI) was also used by Pei et al. (2020) as a comparative parameter in the detection and evaluation of droughts via data from remote products, as the application of SPI can eliminate temporal and spatial differences in precipitation, making droughts comparable in time and space (Liu et al., 2021). For better characterizing and evaluating the impacts of drought on vegetation, Tigkas et al. (2019) developed and applied the aSPI, a more solid and appropriate formulation of the SPI to assess agricultural drought.

However, discussions about the applicability of which index to use, especially in semi-arid climate regions, are common (Li et al., 2020). Therefore, the objective of this study was to monitor the dynamics of agricultural drought, through the response of vegetation, in the semi-arid region that comprises the state of Paraíba, Brazil, through MODIS satellite products applied to the VCI, TCI and VHI indices, and to evaluate the correspondence of VHI index with SPI and aSPI.

Material and Methods

The area used in this study comprises the delimited semi-arid region of the Paraíba state, Brazil (Figure 1) (Brasil, 2017).

The spatial-temporal analysis of droughts in the region was performed through the index that determines the vegetation health condition (VHI), which carries in its composition two indices: the vegetation condition index (VCI) and the temperature condition index (TCI). The analysis was annual, considering the hydrological year of October/September (DNAEE, 1976).

To quantify the impact of moisture and thermal stress on vegetation, the VCI and TCI indices were calculated, respectively, using long-term observations of NDVI (normalized difference vegetation index) and LST (land surface temperature) data derived from the MODIS satellite and collected between 2010 and 2020.

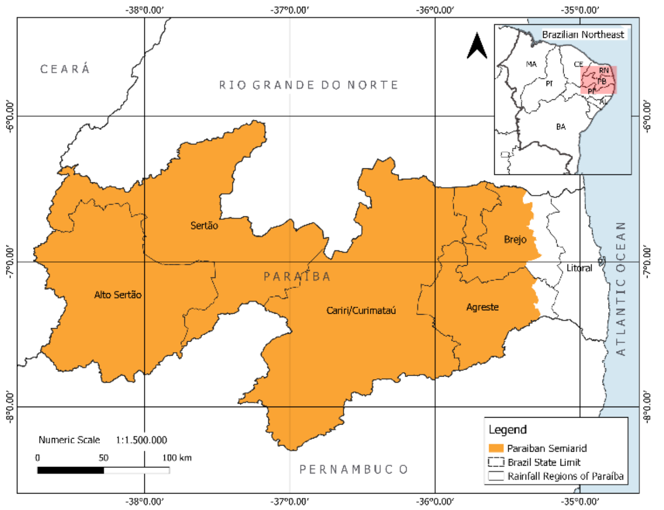


Figure 1. Delimitation of the semi-arid region of Paraíba, Brazil

The MODIS/Aqua products used in this study are MYD09A1 and MYD11A2. The first product consists of images of surface reflectance, with composition of eight days, spatial resolution of 500 m, while the latter refers to surface temperature products, LST day and LST night, at spatial resolution of 1 km and the same temporal resolution as the previous product.

LST day products were used for this study, according to the methodology proposed by Sánchez et al. (2016) and by Souza et al. (2021), who applied the method in a study carried out in the Brazilian state of Pernambuco, which has approximately 88% of its territory located in the semi-arid region.

MODIS images were downloaded using the R program and the Modistsp package dedicated to automating the creation of time series of raster images derived from MODIS Land Products data.

QGis software was used to perform image processing, which involved the generation of 46 NDVI and LST products for each year of study and clipping to highlight the limits of the semi-arid region of Paraíba state.

VCI is derived from the normalized difference vegetation index (NDVI), accounting for its maximum ($NDVI_{max}$) and minimum ($NDVI_{min}$) values (Eq. 1). This not only reflects the variability of vegetation spatially and temporally, but also allows quantifying climatic impacts on vegetation (Unganai & Kogan, 1998; Brito et al., 2018).

$$VCI = \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100 \qquad (1)$$

where:

$NDVI_i$ -NDVI value of the ith month; and,

$NDVI_{max}$ and $NDVI_{min}$ - maximum and minimum NDVI values of each year studied, respectively.

NDVI was obtained by using bands 01 and 02 of the MYD09A1 product (Eq. 2).

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \qquad (2)$$

where:

ρ_{NIR} - reflectance in the band that captures spectral responses in near infrared, band 2 in the case of the MYD09A1 product; and,

ρ_R - reflectance in the red band, band 1 in the case of the MYD09A1 product.

In TCI, initially, the LST datasets (MYD11A2) were resampled for spatial resolution of 500 m and converted from a digital number (DN) to Degrees Celsius (Eq. 3).

$$LST\left(^{\circ}C\right) = 0.02DN - 273.15 \tag{3}$$

where:

LST - land surface temperature (°C);

0.02 - scale factor; and,

DN - digital number of the pixel.

TCI was obtained from the minimum and maximum values of LST (Eq. 4), which in turn portrays the surface properties, such as the water content in the surface soil and evapotranspiration. There is an inverse relationship between the LST and the vegetation condition, which is related to the soil moisture content (Sánchez et al., 2016).

$$TCI = \frac{LST_{max} - LST_i}{LST_{max} - LST_{min}} \times 100 \tag{4}$$

where:

LST_i - is the smoothed weekly temperature from satellite; and

LST_{max} and LST_{min} - multi-year maximum and minimum, respectively.

TCI values range from 0 to 100. Higher TCI values indicate wet conditions, while lower values indicate dry conditions.

In VHI, 'a' and 'b' are the weight coefficients of VCI and TCI (Eq. 5). Since the contribution of humidity and temperature during the vegetative cycle is unknown, it was assumed that the participation of VCI and TCI was equal (Brito et al., 2018).

$$VHI = aVCI + bTCI \tag{5}$$

where:

'a' and 'b' - constant value (0.5); and,

VCI - vegetation condition index and TCI is the temperature condition index.

Based on the obtained values of VCI and VHI, each pixel in the study area was classified in the respective category of drought, according to Kogan (2002).

Pearson's correlation coefficient (r) was calculated to evaluate the relationships between the agricultural drought index (VHI) and the SPI and aSPI indices.

The SPI and aSPI were determined for 42 climatological stations located in the semi-arid region of Paraíba, for a period of 30 years (1990 to 2020). For correlation analysis, the annual values of the indices (SPI-12 and aSPI-12) for the 2010-2020 period were used.

The validations were performed by relating the cells, represented by the pixels in the spatial resolution of 500 m, and the points, represented by the 42 selected stations.

SPI is an indicator that expresses the amount of precipitation in a specific time period and is recommended by the World Meteorological Organization (WMO) to be used on a global scale (Li et al., 2020). In SPI calculations, it is assumed that precipitation variability in a sequence follows a gamma distribution and, after processing the probability of precipitation distribution (Γ) by the means of normal standardization (Eq. 6), a standardized cumulative frequency distribution for precipitation can be applied to classify drought levels.

$$g\left(x\right) = \frac{1}{\beta^{\alpha}\Gamma\left(\alpha\right)} x^{\alpha-1} e^{-x/\beta} \tag{6}$$

where:

α - shape parameter (α > 0);

β - scale parameter (β > 0);

x - effective precipitation value (x > 0); and,

Γ(α) - gamma function, expressed as (Eq. 7).

$$\Gamma\left(\alpha\right) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \tag{7}$$

The maximum likelihood method is used to estimate α and β (Eqs. 8, 9 and 10):

$$\alpha = 1 + \frac{\sqrt{1 + \frac{4A}{3}}}{4A} \tag{8}$$

$$\beta = \frac{\overline{x}}{4A} \tag{9}$$

$$A = \ln\left(\overline{x}\right) - \frac{\sum \ln\left(x\right)}{n} \tag{10}$$

where:

n - length of the data record, and the cumulative probability of a given timescale can be calculated as follows (Eq. 11):

$$G\left(x\right) = \int_0^x g\left(x\right) dx = \frac{\int_0^x x^{\alpha-1} e^{-x/\beta} dx}{\beta^{\alpha}\Gamma\left(\alpha\right)} \tag{11}$$

If t = x/β, Eq. (6) becomes a simplified gamma function (Eq. 12).

$$G\left(x\right) = \frac{\int_0^x t^{\alpha-1} e^{-t} dt}{\Gamma\left(\alpha\right)} \tag{12}$$

Since the gamma distribution is not defined for zero precipitation, the Eq. 13 is used to take into account the cumulative probability of zero effective precipitation (q) (Eq. 13):

$$H(x) = q + (1-q)G(x) \tag{13}$$

For calculating the SPI (Eqs. 14 and 15), the cumulative probability distribution is transformed into a normal distribution using the following approximation.

$$\begin{gathered} SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), 0 < H(x) \le 0.5 \\ t = \sqrt{\ln\left(\frac{1}{H(x^2)}\right)} \end{gathered} \tag{14}$$

$$\begin{gathered} SPI = \left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), 0.5 < H(x) \le 1.0 \\ t = \sqrt{\ln\left(\frac{1}{1 - H(x^2)}\right)} \end{gathered} \tag{15}$$

The coefficients are: c_0= 2.515517, c_1= 0.802853, c_2= 0,.010328, d_1= 1.43278, d_2= 0.189269, d_3= 0.001308.

The calculation of aSPI follows the same methodology used for SPI, replacing only the accumulated precipitation (P) with the effective precipitation (P_e).

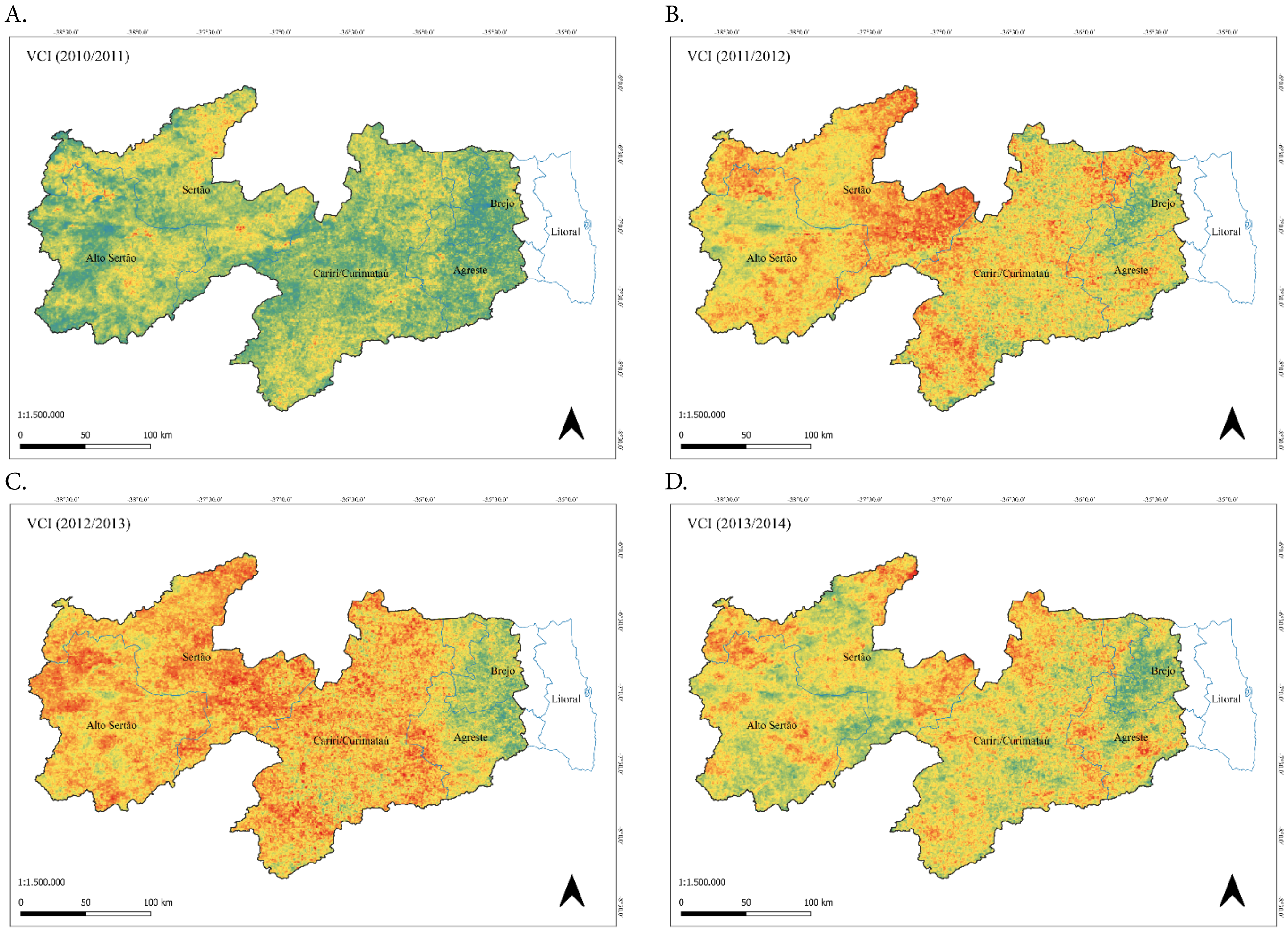
Effective precipitation (Pe) describes more accurately the amount of water that can be used productively by plants, and was estimated by monthly precipitation values, using the US Bureau of Reclamation (USBR) method, as recommended by Tigkas et al. (2019), as it is the method that best applies in semi-arid regions.

The truncation limit used to define a drought event from the values of the indices SPI and aSPI was -0.5, that is, the drought begins when the value of each index is lower than or equal to -0.5 and ends when it approaches zero, progressing to a positive value.

Results and Discussion

The annual VCI drought maps for the study area are shown in Figures 2A, B, C, D, E, F, G, H, I and J. The VCI was interpreted directly, that is, the corresponding VCI values result in stress conditions in the vegetation.

Vegetation plays an important role in the energy exchange of the land's surface, in the hydrological cycle and in climate regulation (Li et al., 2021). Vegetation patterns are sensitive to changes in the ecological environment, that is, lack of precipitation is the main limiting factor, and semi-arid regions



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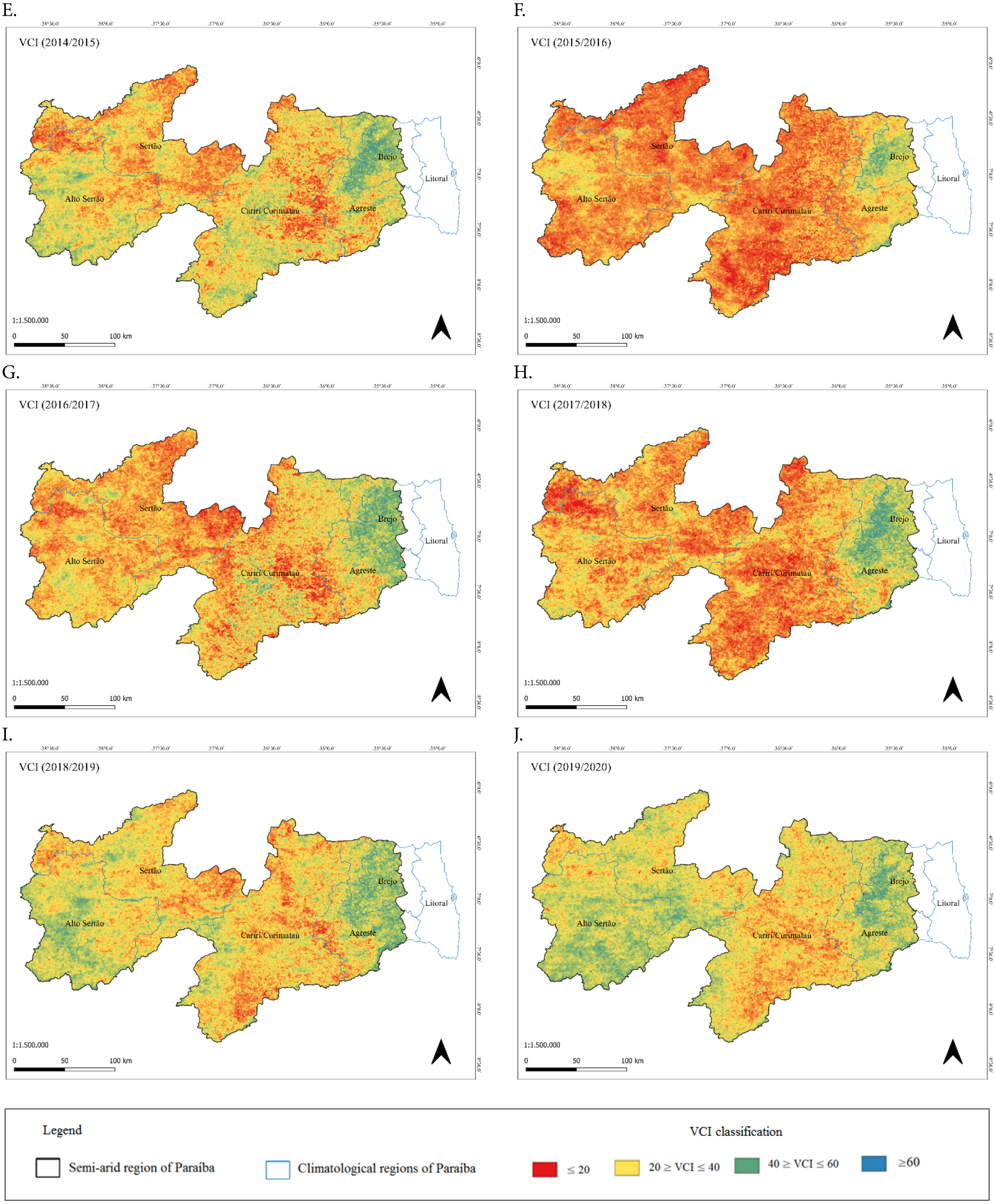


Figure 2. Spatial-temporal variation of the vegetation condition index (VCI) of the semi-arid region of Paraíba between 2010 and 2020

are highly sensitive to variation in precipitation (Zhang et al., 2014).

The results obtained through the VCI index revealed that, in the decade, the region experienced significant reductions in vegetation, especially in the Cariri/Curimataú, Sertão and Alto Sertão regions. The least affected region was the Brejo Paraibano region.

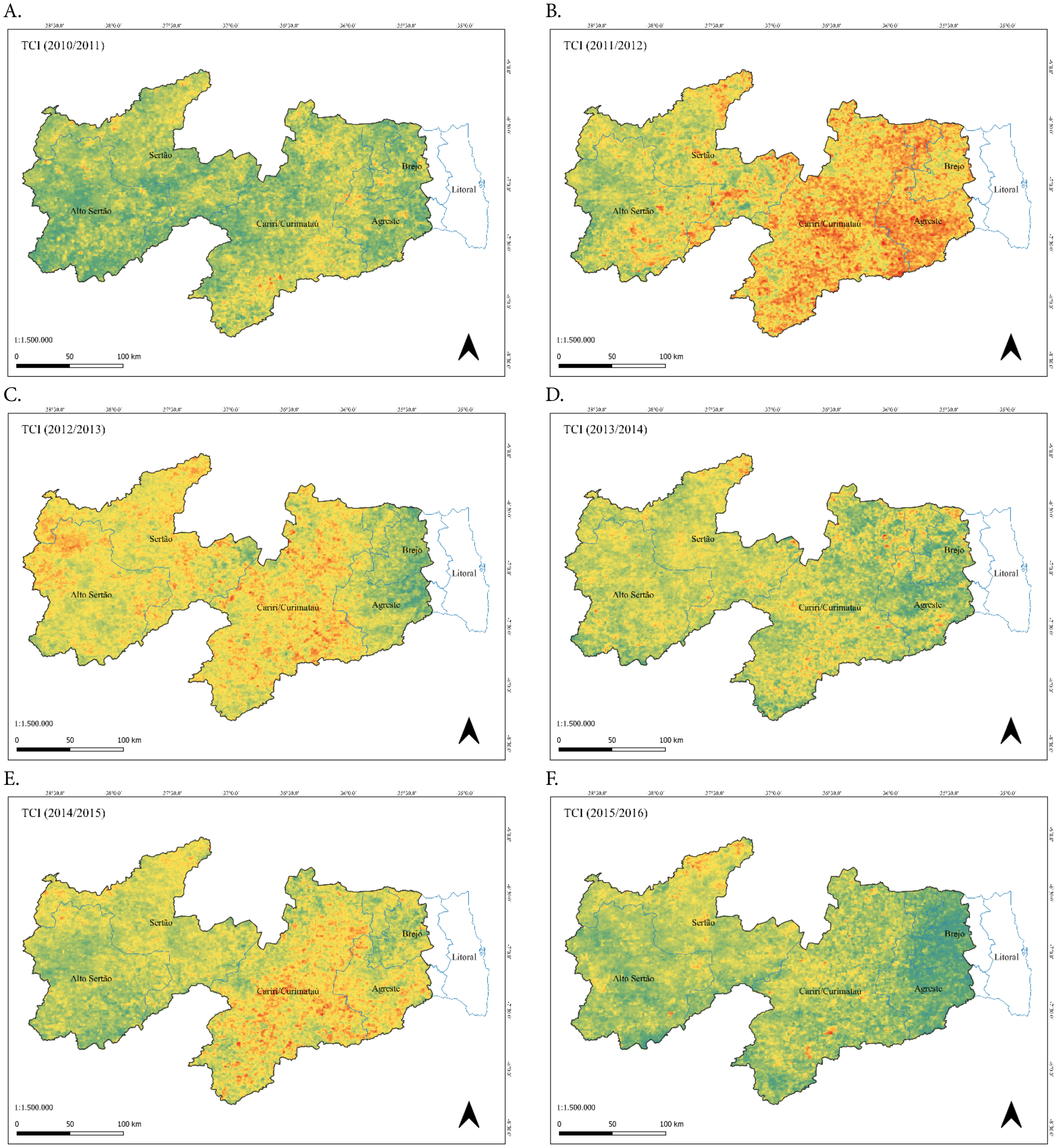
The hydrological year 2010-2011 had high vegetative cover, after which there was a great decline in vegetation vigor (Figure 2A). The year 2015-2016, on the other hand, was the hydrological year that most reflected the response of vegetation to drought, because a period of scarcity of precipitation influenced by the abnormally warm North Tropical Atlantic has already started since 2011-2012 (Marengo et al., 2017), which has led to the decline in soil moisture content (Figure 2F).

The spatial distribution of the land's surface temperature condition is shown in Figures 3A, B, C, D, E, F, G, H, I and J. LST is a parameter used to evaluate the evapotranspiration of the vegetation canopy and soil moisture (Karnieli et al., 2010), applied in the calculation of the TCI. TCI is not interpreted directly. A low TCI value (≤ 40) indicates high and extreme values of surface temperature (LST), which stress vegetation, while a high TCI (≥ 40) indicates favorable conditions for the crop (Kogan, 1997).

The year 2011-2012 had the highest thermal stress, especially in the Cariri/Curimataú, Agreste and Brejo regions, with values ≤ 20 (Figure 3B).

Gomes et al. (2019) inferred that, in the semi-arid region of northeastern Brazil, stressed vegetation features predominate and also observed that the value of TCI in El Niño years was lower than 40 due to irregularity of precipitation in the region.

Gomes et al. (2020) analyzed the relationship between the TCI and VCI indices and the surface air temperature in three cities of Ceará (Fortaleza, Jaguaruana and Campos Sales).



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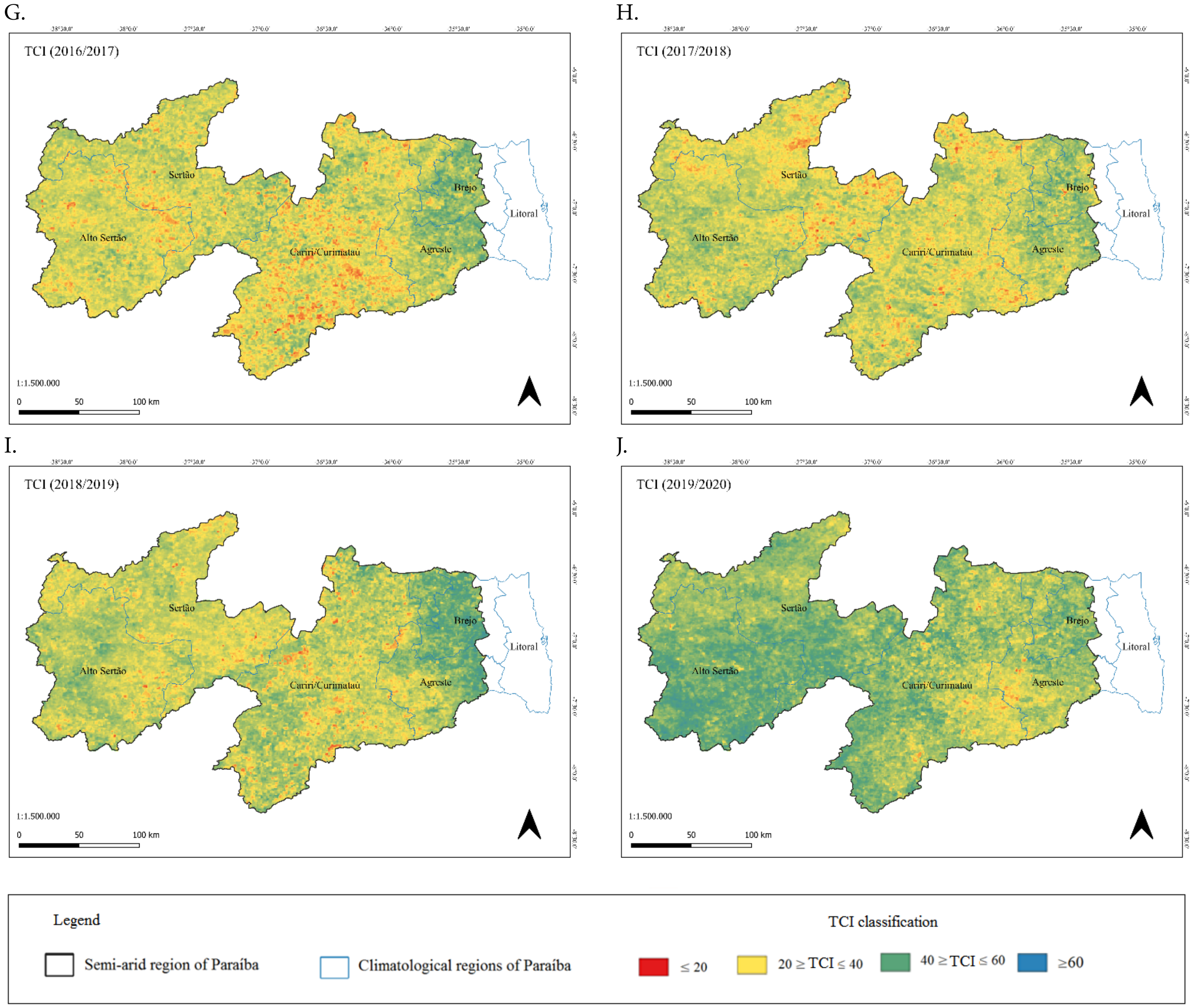


Figure 3. Spatial-temporal variation of the temperature condition index (TCI) of the semi-arid region of Paraíba between 2010 and 2020

Their results showed a strong correlation with great statistical significance, proving that TCI and VCI are indicative of thermal conditions in the studied regions and that they can be used as a "drought watch" according to Kogan (1997).

The values of VCI and TCI showed that the vegetation of the study region was under strong water stress. The combination of these parameters through VHI confirms that the study area experienced a characteristic period of agricultural drought between 2010 and 2020.

VHI is a popular and effective satellite index in the monitoring of agricultural drought (Hu et al., 2020; Li et al., 2020). This is because VHI and crop yields are highly correlated, especially in the critical growth stage (Kogan et al., 2012).

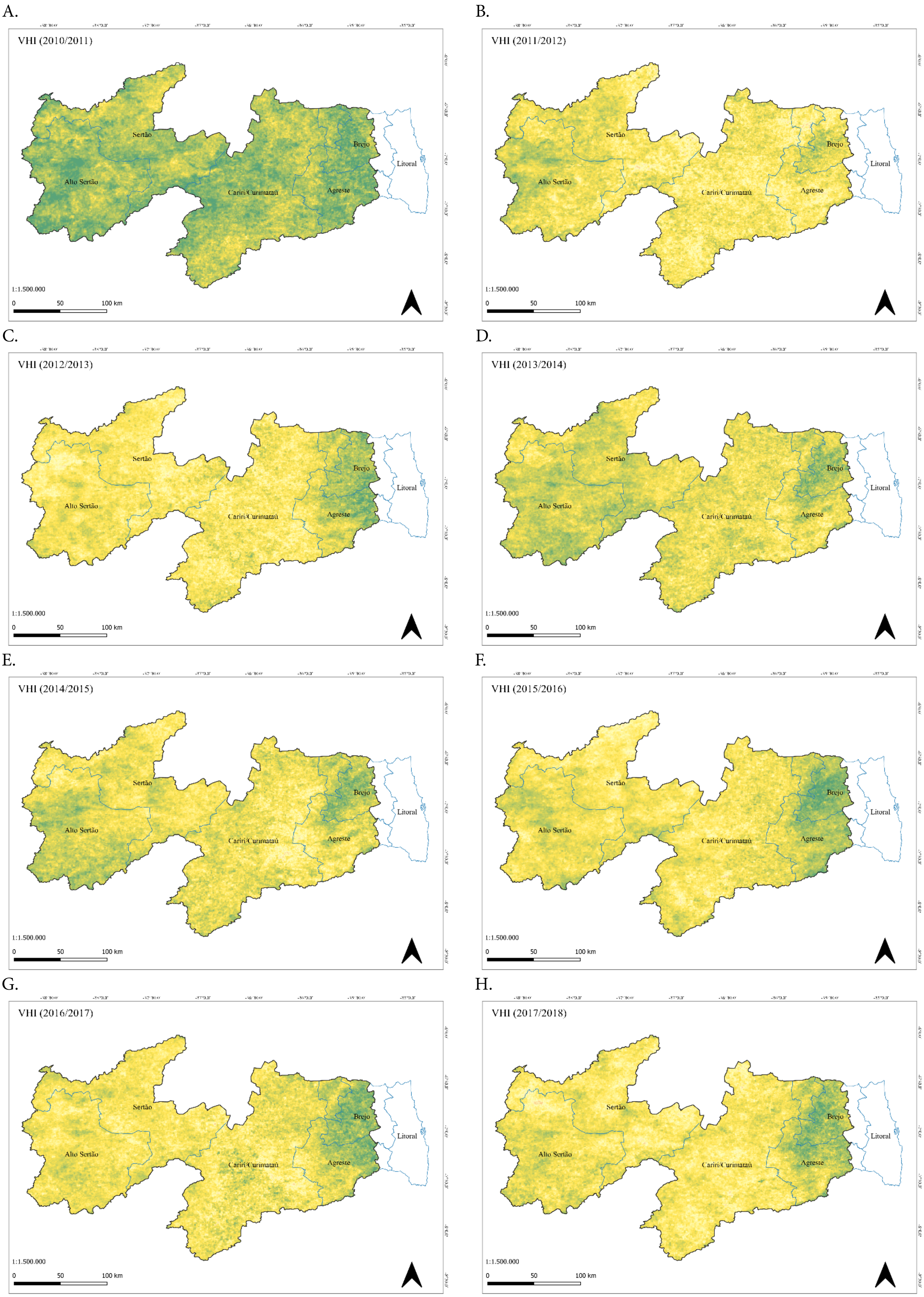
The annual maps of the spatial distribution of VHI for the study area from 2010 to 2020 are shown in Figures 4A, B, C, D, E, F, G, H, I and J. The lower the VHI value, the more severe the drought, which confirms that the study area underwent a large agricultural drought during the studied period.

In the year 2011-2012, a period of drought on a mild and moderate scale was observed, where the mean value of annual VHI was lower than 20 and covered almost completely the study area (Figure 4B). There is also a trend over time for the same drought conditions. Only the region that corresponds to Brejo showed recovery of vegetation vigor, having normal VHI indices (≥ 40).

The VHI distribution indicates that the Cariri/Curimataú, Agreste, Sertão and Alto Sertão regions were severely affected by droughts, while the Brejo region was the least affected over the study period (Figure 4).

Degefu & Bewket (2015) suggest that typically, episodes of severe and extreme drought cover larger areas, while episodes of mild and moderate drought tend to affect localized areas, but our study indicated that mild and moderate droughts may be spatially distributed throughout a region.

In view of the above results, it can be seen that the study period was marked by a strong hydrometeorological imbalance that resulted in significant damage to agricultural



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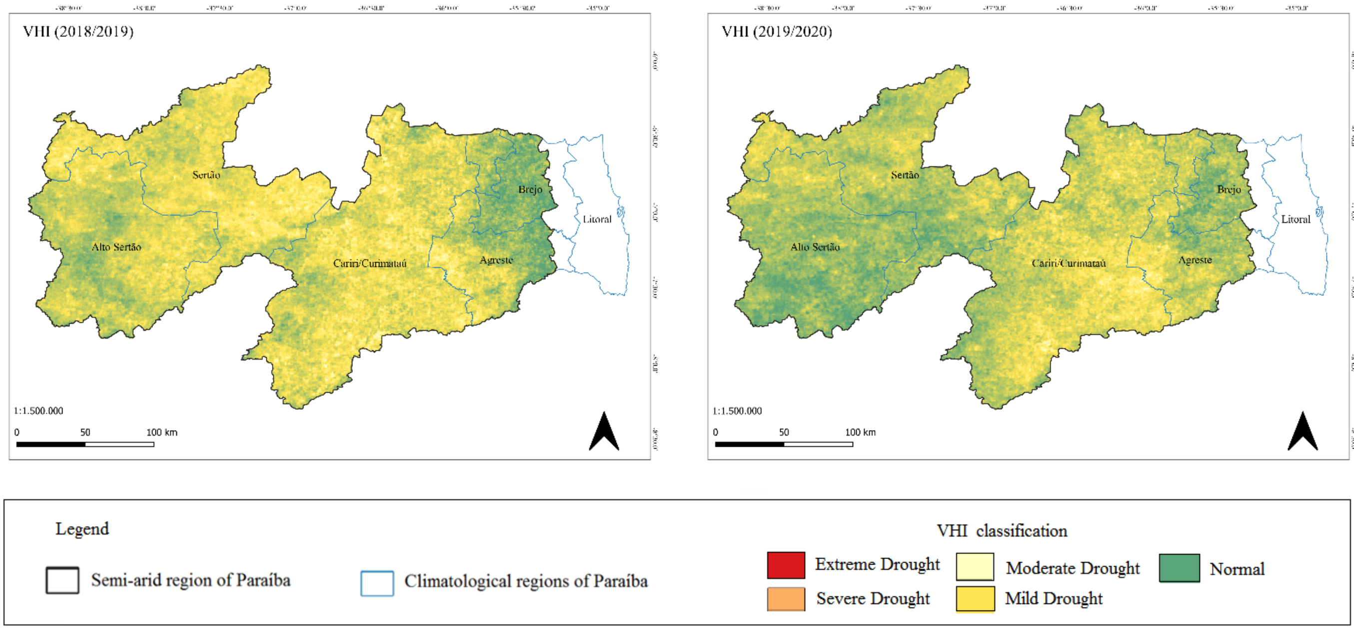

Figure 4. Spatial-temporal variation of the vegetation health index (VHI) of the semi-arid region of Paraíba between 2010 and 2020

production and human subsistence. Inocêncio et al. (2020), in the analysis of drought events in the state of Pernambuco, reported that indices based on soil moisture obtained via remote sensing allowed the evaluation of the drought phenomenon in the period of 30 years, showing an increase from the year 2012, which was more accentuated in the semi-arid region of the state. Thus, it is possible to affirm that agricultural drought is caused by the scarcity of a sufficient amount of soil moisture, which affects plant growth and development.

During these years of drought, the impact spread directly and indirectly to almost all regions, costing the livelihood of most families in the state and thus affecting all sectors of the economy. Data from IBGE (2023) show that there was reduction of about 45% of planted area in the state of Paraíba, from the beginning of 2010 to 2020, precisely in the regions most affected by drought: Cariri/Curimataú, Agreste, Sertão and Alto do sertão.

Ding et al. (2020) claim that agricultural and meteorological droughts have large impacts on vegetation. Therefore, Marengo et al. (2021) suggest the adoption of strategies of adaptation to the expected increase in the incidence of droughts, thus making it possible to reduce the impacts and damage caused, especially for small producers.

Table 1 shows the correlations between the mean annual VHI values and the SPI and aSPI drought indices (on the 12-month scale). VHI was chosen because it allows quantifying vegetation health under thermal conditions (Kogan et al., 2012), while SPI and aSPI are recommended in studies on semi-arid regions (Tigkas et al., 2019).

VHI showed a significantly strong correlation for the SPI and aSPI indices in all microregions studied, except in the Brejo region, where VHI x aSPI did not respond significantly ($r \leq 0.5$). This may be due to the soil characteristics of the region, predominantly Podzólico vermelho-amarelo equivalente

Table 1. Correlation between the vegetation health index (VHI) and standardized precipitation index (SPI) and agricultural standardized precipitation index (aSPI)

Climatologial of Paraíba	Pearson's correlation with VHI index (r)	
	SPI	aSPI
Agreste	0.658*	0.733*
Brejo	0.502	0.468
Cariri/Curimataú	0.866*	0.858*
Sertão	0.765*	0.814*
Alto Sertão	0.665*	0.718*

* Significant by t test at $p \leq 0.05$

eutrófico (EMBRAPA, 2017), which can retain soil moisture and maintain vegetation support.

The r value was higher in the correlation of VHI and aSPI, because the index uses the effective precipitation in its calculation, which characterizes the actual value of the utilization of precipitated water by the vegetation.

The degree of correlation was higher in the regions where the most severe drought events occurred, such as the Cariri/Curimataú region.

In the studies of Pei et al. (2020) and Javed et al. (2020), the response of vegetation to drought was also significant, which means that vegetation growth may reflect the degree of drought of a region.

Conclusions

1. In the semi-arid region of Paraíba between 2010 and 2020, characteristics of stressed vegetation predominated, due to irregularity of precipitation and high temperatures, confirming the possibility of detecting droughts using VHI, VCI and TCI.

2. Indices detected remotely and through local data have a strong correlation in the detection of droughts, indicating that VHI can characterize well the development of vegetation responses to drought in the semi-arid region of Paraíba.

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Literature Cited

Brasil - Ministério da Integração Nacional. Nova delimitação do semiárido brasileiro. Brasília, 2017. Available on: <https://www.in.gov.br/materia/-/asset_publisher/Kujrw0TZC2Mb/content/id/739568/do1-2017-12-05-resolucao-n-115-de-23-de-novembro-de-2017-739564>. Accessed on: Oct. 2019.

Brasil Neto, R. M.; Santos, C. A. G.; Silva, J. F. C. B. da C.; Silva, R. de M. da; Santos, C. A. C. dos; Mishra, M. Evaluation of the TRMM product for monitoring drought over Paraíba State, northeastern Brazil: a trend analysis. Scientific Reports, v.11, p.1-18, 2021. https://doi.org/10.1038/s41598-020-80026-5

Brito, S. S. B.; Cunha, A. P. M.; Cunningham, C. C.; Alvalá, R. C., Marengo, J. A., Carvalho, M. A. Frequency, duration and severity of drought in the Semiarid Northeast Brazil region. International Journal of Climatology, v.38, p.517-529, 2018. https://doi.org/10.1002/joc.5225

Degefu, M. A.; Bewket, W. Trends and spatial patterns of drought incidence in the omo-ghibe river basin, ethiopia. Geografiska Annaler: Series A, Physical Geography, v.97, p.395-414, 2015. https://doi.org/10.1111/geoa.12080

Ding, Y.; Xu, J.; Wang, X.; Peng, X.; Cai, H. Spatial and temporal effects of drought on Chinese vegetation under different coverage levels. Science of The Total Environment, v.716, p.1-12, 2020. https://doi.org/10.1016/j.scitotenv.2020.137166

DNAEE - Departamento Nacional de Águas e Energia Elétrica. Glossário de termos hidrológicos. Brasília: DNAEE, 1976. 291p.

EMBRAPA - Empresa Brasileira de Pesquisa Agropecuária. Mapa exploratório - reconhecimento de solos do estado da Paraíba, 2017. Available on: <http://geoinfo.cnps.embrapa.br/layers/geonode%3Asolos_paraiba_wgs84_1>. Accessed on: Jan. 2022.

Gomes, A. R. dos S.; Alves, J. M. B.; Silva, E. M. da; Gomes, M. R. dos S.; Gomes, C. R. dos S. Estudo da relação entre a variabilidade dos índices de vegetação e temperatura da região Nordeste do Brasil. Revista Brasileira de Meteorologia, v.34, p.359-368, 2019. https://doi.org/10.1590/0102-7786343051

Gomes, A. R. dos S.; Braga, V. B., Alves; J. M. B.; Silva, E. M. da; Gomes, C. R. dos S.; Gomes, M. R. dos S. Análise de estresse vegetativo, associado às variáveis climáticas no Nordeste do Brasil e nos municípios do Ceará >/> (Fortaleza, Jaguaruana e Campos Sales). Revista Brasileira de Meteorologia, v.35, p.493-504, 2020. https://doi.org/10.1590/0102-77863530013

Hu, T.; van Dijk A. I.; Renzullo, L. J.; Xu, Z.; He, J.; Tian, S.; Zhou, J.; Li, H. On agricultural drought monitoring in Australia using Himawari-8 geostationary thermal infrared observations. International Journal of Applied Earth Observation and Geoinformation, v.91, p.1-13, 2020. https://doi.org/10.1016/j.jag.2020.102153

IBGE - Instituto Brasileiro de Geografia e Estatística. Levantamento Sistemático da Produção Agrícola - LSPA. Available on: <https://sidra.ibge.gov.br/tabela/6588>. Accessed on: Feb. 2023.

Inocêncio, T. de M.; Ribeiro Neto, A.; Souza, A. G. S. S. Soil moisture obtained through remote sensing to assess drought events. Revista Brasileira de Engenharia Agrícola e Ambiental, v.24, p.575-580, 2020. https://doi.org/10.1590/1807-1929/agriambi.v24n9p575-580

Javed, T.; Yao, N.; Chen, X.; Suon, S.; Li, Y. Drought evolution indicated by meteorological and remote-sensing drought indices under different land cover types in China. Environmental Science and Pollution Research, v.27, p.4258-4274, 2020. https://doi.org/10.1007/s11356-019-06629-2

Karnieli, A.; Agam, N.; Pinker, R. T.; Anderson, M.; Imhoff, M. L.; Gutman, G. G.; Panov, N.; Goldberg, A. Use of NDVI and land surface temperature for drought assessment: Merits and limitations. Journal of climate, v.23, p.618-633, 2010. https://doi.org/10.1175/2009JCLI2900.1

Kogan, F. Global drought watch from space. Bulletin of the American Meteorological Society, v.78, p.621-636, 1997. https://doi.org/10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2

Kogan, F. World droughts in the new millennium from AVHRR-based vegetation health indices. Eos, Transactions American Geophysical Union, v.83, p.557-563, 2002. https://doi.org/10.1029/2002EO000382

Kogan, F.; Salazar, L.; Roytman, L. Forecasting crop production using satellite-based vegetation health indices in Kansas, USA. International journal of remote sensing, v.33, p.2798-2814, 2012. https://doi.org/10.1080/01431161.2011.621464

Kukunuri, A. N. J.; Murugan, D.; Singh, D. Variance based fusion of VCI and TCI for efficient classification of agriculture drought using MODIS data. Geocarto International, v.37, p.1-22, 2020. https://doi.org/10.1080/10106049.2020.1837256

Li, Y.; Zhao, Z.; Wang, L.; Li, G.; Chang, L.; Li, Y. Vegetation changes in response to climatic factors and human activities in Jilin Province, China 2000-2019. Sustainability, v.13, p.1-16, 2021. https://doi.org/10.3390/su13168956

Li, Y.; Strapasson, A.; Rojas, O. Assessment of El Niño and La Niña impacts on China: Enhancing the early warning system on food and agriculture. Weather and Climate Extremes, v.27, p.1-13, 2020. https://doi.org/10.1016/j.wace.2019.100208

Liu, C.; Yang, C.; Yang, Q.; Wang, J. Spatiotemporal drought analysis by the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI) in Sichuan Province, China. Scientific Reports, v.11, p.1-14, 2021. https://doi.org/10.1038/s41598-020-80527-3

Marengo, J. A.; Torres, R. R.; Alves, L. M. Drought in Northeast Brazil past, present, and future. Theoretical and Applied Climatology, v.129, p.1189-1200, 2017. https://doi.org/10.1007/s00704-016-1840-8

Marengo, J. A.; Galdos, M. V.; Challinor, A.; Cunha, A. P.; Marin, F. R.; Vianna, M. D. S.; Alvala, R. C. S.; Alves, L. M.; Moraes O. L.; Bender, F. Drought in Northeast Brazil: A review of agricultural and policy adaptation options for food security. Climate Resilience and Sustainability, v.1, p.1-20, 2021. https://doi.org/10.1002/cli2.17

Pei, Z.; Fang, S.; Wang, L.; Yang, W. Comparative analysis of drought indicated by the SPI and SPEI at various timescales in inner Mongolia, China. Water, v.12, p.1-20, 2020. https://doi.org/10.3390/w12071925

Sánchez, N.; González-Zamora, Á.; Piles, M.; Martínez-Fernández, J. A new Soil Moisture Agricultural Drought Index (SMADI) integrating MODIS and SMOS products: a case of study over the Iberian Peninsula. Remote Sensing, v.8, p.1-25, 2016. https://doi.org/10.3390/rs8040287

Souza, A. G. S. S.; Ribeiro Neto, A.; Souza, L. L. de. Soil moisture-based index for agricultural drought assessment: SMADI application in Pernambuco State-Brazil. Remote Sensing of Environment, v.252, p.1-15, 2021. https://doi.org/10.1016/j.rse.2020.112124

Svoboda, M. D.; Fuchs, B. A. Handbook of drought indicators and indices. Geneva, Switzerland: World Meteorological Organization, 2016. 44p.

Tigkas, D.; Vangelis, H.; Tsakiris, G. Drought characterisation based on an agriculture-oriented standardised precipitation index. Theoretical and Applied Climatology, v.135, p.1435-1447, 2019. https://doi.org/10.1007/s00704-018-2451-3

Unganai, L. S.; Kogan, F. N. Drought monitoring and corn yield estimation in Southern Africa from AVHRR data. Remote sensing of environment, v.63, p.219-232, 1998. https://doi.org/10.1016/S0034-4257(97)00132-6

Zhang, B.; Zhu, J. J.; Liu, H. M.; Pan, Q. M. Effects of extreme rainfall and drought events on grassland ecosystems. Chinese Journal of Plant Ecology, v.38, p.1-12, 2014. https://doi.org/10.3724/SP.J.1258.2014.00095