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Temporal analysis of drought coverage in a watershed area using remote sensing spectral indexes

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Abstract
The development of several time series analysis programs using satellite images has provided many applications based on resources from geostatistics field. Currently, the use of statistical tests applied to vegetation indexes has enabled the analysis of different natural phenomena, such as drought events in watershed areas. The objective of this article is to provide a comparative analysis between NDVI and EVI vegetation index data made available by MOD13Q1 project of MODIS sensor for drought mapping using vegetation condition index (VCI) in the Serra Azul stream sub-basin, MG. The methodology adopted the Cox-Stuart statistical test for seasonality analysis and Pearson's linear correlation to verify the influence of different indexes on delimitation of drought in a watershed. The results indicated the NDVI vegetation index as more efficient than EVI in spatial characterization of studied watershed region, mainly in identification of seasonality. The VCI proved to be highly feasible for monitoring drought in study period between 2013 and 2018, allowing the effective delimitation of drought conditions in the Serra Azul stream sub-basin. In addition, the effectiveness of MODIS sensor data in characterizing drought events that affected the study area was proven.

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INTRODUCTION

The development of several Earth observation programs has provided, through spectral analyzes of the environment, increasingly adequate responses to different natural variations and anthropogenic actions that occur on planet´s surface. One of the important factors that helped in expansion of this knowledge is data recording in time series that make it possible to analyze the records of patterns related to different processes, such as biogeophysical, meteorological and other cycles (POTTER et al., 2003).

The concept of time series comes from the set of observations recorded over a given time interval. In the scope of environmental sciences, the availability of this type of data allows the development of several applications, such as rain or air temperature analysis using probabilistic or holistic approaches. In recent times, remote sensing technology has contributed significantly to these analyzes due to its characteristic ability to produce databases containing information from Earth's surface in the form of time series (DAVIES; CHATFIELD, 1990; SAUSEN; LACRUZ, 2015).

In time series analysis, remote sensing data applications can be performed from the perspective of earth's surface analysis, through variables that are used directly in drought monitoring such as vegetation indexes (DECHANT; MORADKHANI, 2014, 2015). Vegetation indexes are mathematical formulations that use remote sensing spectral data to estimate the behavior of vegetation cover in a region. These formulations allow to analyze the vegetation activity as well as foliage variation in terms of seasonality (BONIFACIO; DUGDALE; MILFORD, 1993; FORMAGGIO, SANCHES, 2017).

The analysis of spatial variability of data to obtain estimates in non-sampled locations is performed using geostatistics. In this process, exploratory techniques based on descriptive analysis of calculations from descriptive statistics are used. In time series research field, trend analysis is of great relevance in environmental matters, as they are able to identify the influence of seasonality on some parameters under study (SOARES, 2000; VIEIRA et al., 1983). In these types of studies, the MODIS sensor has been widely used in research involving sugarcane species, with use of drought rates (DUFT; PICOLI, 2018), as well as in studies on pasture areas (CUNHA et al., 2017).

Currently, several studies use time series analysis with vegetation index data to monitor natural disasters, such as drought and water scarcity in river basins. In studies related to drought, the vegetation indexes are applied to monitor the event through the Vegetation Condition Index (VCI), created by Kogan (1995), and applied using MODIS sensor data in event analysis of drought in biological reserves (BRANCO, 2016), as well as in comparison between drought delimitation indexes (JIAO et al., 2019; ZHANG et al., 2017). In addition, this technique is applied with the use of other remote sensing data, such as NOAA-NESDIS, in analyzes of vegetation tendency to drought variation (XU et al., 2020) and variability of vegetation and temperature indexes in Brazilian regions (GOMES et al., 2019).

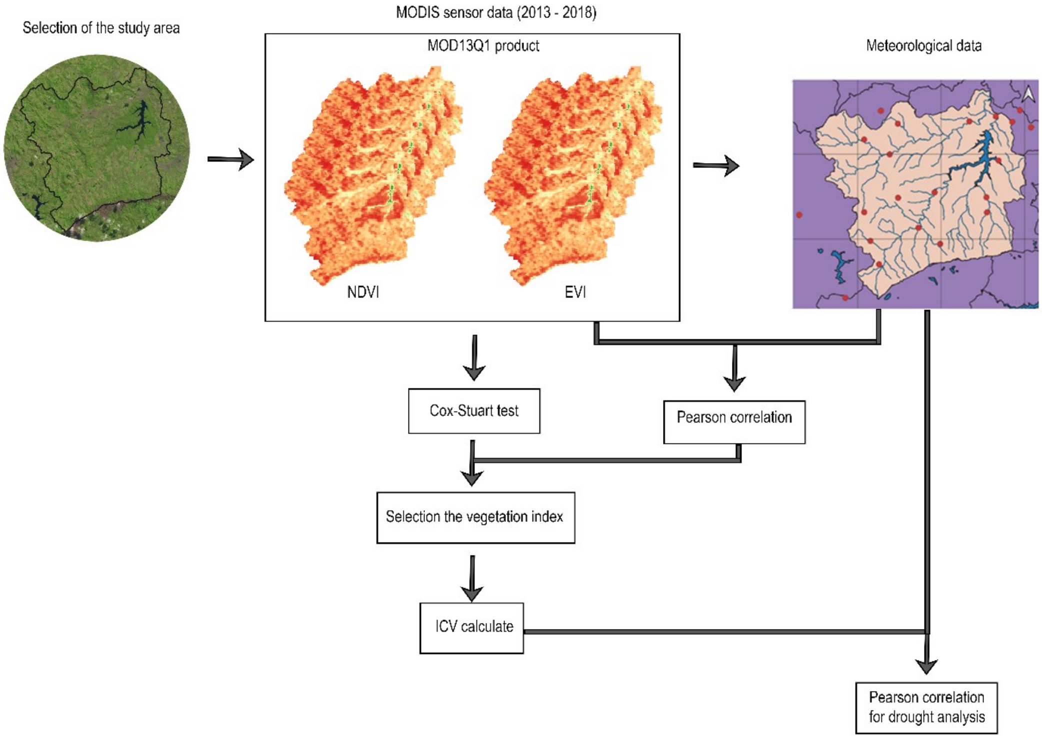
In remote sensing researches, within geostatistics scope, the Cox-Stuart test can assess time series tendency to present seasonality through the application of a Ho hypothesis. The trend is calculated through the differences between pairs of time series variables, extracted from the original sample of time series. A positive or negative sign is associated with each pair, and equal values are eliminated. In the Ho hypothesis, the total number of negative and positive signs is expected to be similar, so that a series is considered to be trendless (COX; STUART, 1955; DETZEL et al., 2011). The application of this technique has been developed in studies that use data from MODIS sensor (ARANTES et al., 2017) and in assessment of vegetation behavior for environmental planning and sustainable management with SPOT data (CHAVES; MATAVELI; JUSTINO, 2014).

The objective of this work is to provide a comparative analysis between data of normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) available in MOD13Q1 project of MODIS sensor for drought mapping by determining the vegetation condition index (VCI). The adopted approach involved the application of Cox-Stuart statistical test for seasonality analysis and the use of Pearson's linear correlation to verify the indexes influence in the Serra Azul stream basin drought delimitation.

METHODS

The drought variation was identified through data from the MOD13Q1 product, the methodology used was divided into five analyzes, namely: selection of the study area, obtaining data from the MODIS sensor, analysis of the vegetation indexes time series, calculation of the vegetation condition index and correlation of the results generated with meteorological data (Figure 1).

Figure 1 - Flowchart of the applied methodology.



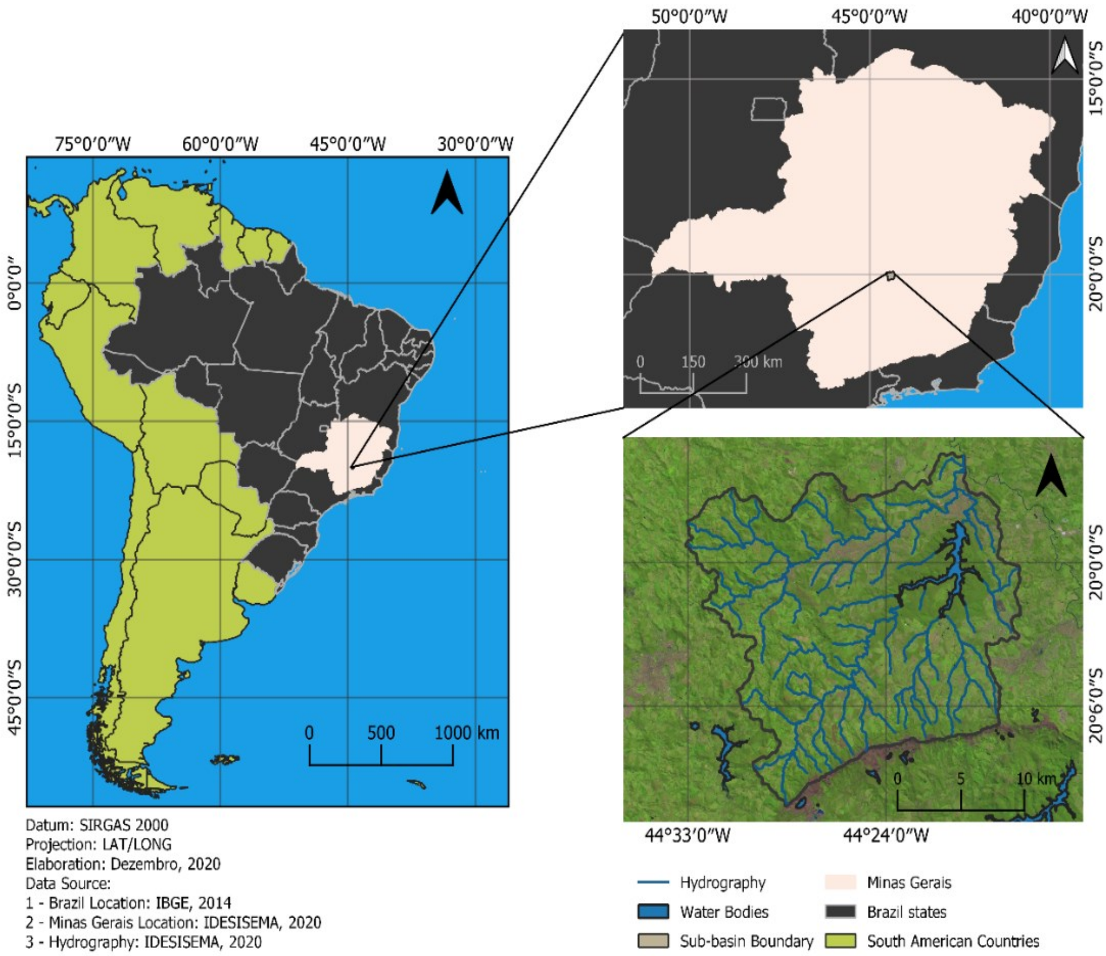
Source: The Authors.

Drought analysis in the Serra Azul stream sub-basin

The study area is the Serra Azul stream sub-basin which covers 447.83 km² of drainage area along the municipalities of Mateus Leme, Igarapé, Juatuba and Itaúna (Figure 2). The region is located in state of Minas Gerais, Brazil between 20º 15' and 20º 00' south latitude parallels and 44º 15' and 44º 35' west longitude meridians. Inside this basin there is a supply reservoir owned by Companhia de Saneamento de Minas Gerais (COPASA), responsible for water supply of Belo Horizonte city and adjacent locations (DUTRA; BRIANEZI; COELHO, 2020; DUTRA; ELMIRO; GARCIA, 2020).

According to the Köeppen classification, the region has an Aw-type climate. The "A" refers to the tropical summer, that is, areas with an average monthly temperature above 18ºC. The "w" means that the region has a period of four to six months of dry season (DUBREUIL et al., 2018). According to IBGE climate classification (IBGE, 2019), the region is inserted in Tropical Zone Central Brazil Sub-hot, semi-humid with four to five dry months that characterizes it as semi-humid.

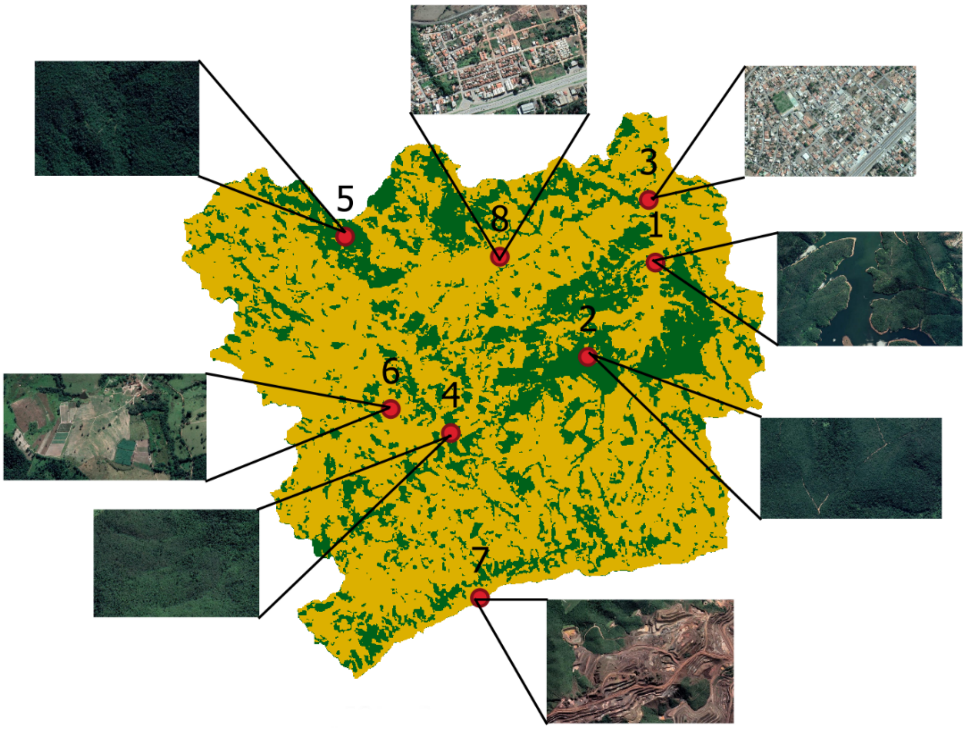
Figure 2 - Serra Azul stream sub-basin location



Source: The Authors.

In relation to land use, the study area is located in the Alto São Francisco region, which is characterized by Rock vegetation and Atlantic forest in the neighborhood of water supply reservoir. In addition, the region is under a large intervention of human activities, due to the expansion of urban areas, agricultural activities and mining (Figure 3). These activities cause the suppression of vegetation, impermeability of the soil and several impacts in the region, such as increased surface temperature and water scarcity events (DUTRA; BRIANEZI; COELHO, 2020; DUTRA; ELMIRO; GARCIA, 2020; MINAS-GERAIS, 2015).

Figure 3 - Variation of land use in the Serra Azul stream sub-basin, with the presence of the following points: 1 (Serra Azul reservoir); 2, 5 and 4 (forest area); 3 and 8 (urban area); 6 (agriculture); and 7 (mining area), where the green areas correspond to vegetation regions and the yellow areas are non-forest



Source: Dutra, Elmiro and Garcia (2020).

MODIS sensor data

The data from MODIS sensor was obtained on United States Geological Survey (USGS) platform. Originally, the images are provided in Hierarchical Data Format (HDF) ,sinusoidal cartographic projection and 250m spatial resolution. In this way, QGIS 3.4.6 software tools were used to convert data to Tagged Image File Format (TIFF) and UTM (Universal Transverse Mercator) cartographic projection, 23 South Zone and SIRGAS 2000 horizontal datum. The project data are expressed in the range of -10000 to 10000, therefore it was necessary to reschedule data using a scale factor (0.0001) to obtain vegetation indexes values in conventional numerical range from -1 to 1.

Analysis of vegetation indexes time series: Cox-Stuart test

For application of the proposed statistical analyzes, a monthly based time series was created for the period between 01/01/2013 and 12/31/2018, corresponding to 72 months. Vegetative vigor information for each pixel was extracted from this monthly time series, referring to location of meteorological stations of the Instituto Nacional de Meteorologia (INMET) and Agência Nacional de Águas (ANA). Figure 4 shows the location of these stations.

In order to verify the existence of some tendency to seasonality in relationship between amplitude and mean of time series data, the Cox-Stuart test was applied, using RStudio software. This test developed by Cox and Stuart (1955) was applied in studies of Morettin and Toloi (2006). According to Morettin and Toloi (1981), in applications of time series analysis referring to vegetation index data, the test aims to assess whether or not a time series presents trends in seasonality using the following hypotheses:

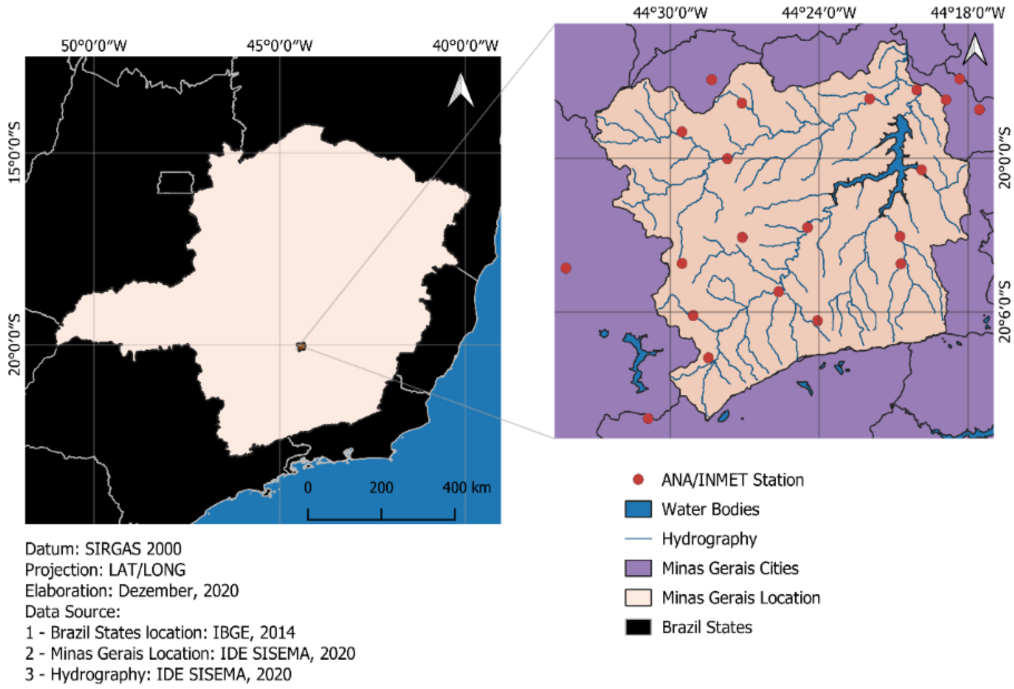
H_0: no trend, the number of positive and negative signs are equal.
H_1: trend, the number of positive and negative signs are different.

Vegetation condition index (VCI) calculation

In order to analyze the occurrence of drought using vegetation condition index

(VCI), the data referring to vegetation index that showed the best response in statistical analyzes were organized according to seasons (Table 1). Dates were sorted in ascending order according Julian days (continuous scale of the days of the year).

Figure 4 - Location of ANA and INMET stations



Source: The Authors.

Table 1 - Seasons, Julian days and Gregorian days referring to vegetation indexes images obtained from MODIS sensor.

SUMMER	**AUTUMN**	**WINTER**	**SPRING**
-	81 – 22/03	177 – 26/06	273 – 30/09
01 – 01/01	97 – 07/04	193 – 12/07	289 – 16/10
17 – 17/01	113 – 23/04	209 – 28/07	305 – 01/11
33 – 02/02	129 – 09/05	225 – 13/08	321 – 17/11
49 – 18/01	145 – 25/05	241 – 29/08	337 – 03/12
65 – 06/03	161 – 10/06	257 – 14/09	353 – 19/12

Source: The Authors.

Vegetation changes are not easily identified with direct use of vegetation indexes, so VCI is used, as a more effective index, in order to identify the productivity of an ecosystem. The VCI measures drought condition according to interference of climate in vegetative vigor of a region (DU et al., 2013). For preparation of VCI, the averages of NDVI and EVI were calculated for each season throughout the analyzed period (2013 a 2018), according to Equation 1.

$$\bar{X} = \frac{1}{NI} \sum_{i=1}^{NI} Xiv \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where

NI = number of images for each season;
$\bar{X}$ = average of a numerical data set; and
Xiv = vegetation index values.

In order to obtain the drought occurrences over the full studied period, the methodology proposed by Kogan (1995a) was applied, according to Equation 2. First, the average images were grouped according to season, throughout the entire time series. Then, the average of all pixels referring to maximum and minimum values for each season was calculated for each type of vegetation index.

$$VCI = \frac{\bar{X}_e - \bar{X}_{mine}}{\bar{X}_{maxe} - \bar{X}_{mine}} * 100 \quad (2)$$

where
VCI = Vegetation Condition Index (%);
$\bar{X}_e$ = average per season of vegetation index for a given year;
$\bar{X}_{mine}$ = overall average of minimum values of vegetation index for a given season; and
$\bar{X}_{maxe}$ = overall average of maximum values of vegetation index for a given season.

The VCI, presenting values from zero to one hundred, allows analysis of vegetation index data (NDVI and EVI) in a short period of time, as well as the evaluation of changes in long term. According to Kogan (1995a), the closer de VCI value to zero the greater the influence of drought phenomenon in a region. Following this approach, drought is classified according to Table 2.

Table 2 - Class ranges of Vegetation Condition Index (VCI) values and the corresponding classification

VCI VALUES (%)	CLASSIFICATION
X < 20	Extreme Drought
20 ≤ X < 40	Severe Drought
40 ≤ X < 60	Moderate Drought
60 ≤ X < 80	Mild Drought
X ≥ 80	No Drought Occurrence

Source: Modified from Bhuiyan and Kogan (2010) and Covele (2011).

Correlation between meteorological data and NDVI, EVI and VCI indexes

A correlation analysis between vegetation indexes and meteorological data was used to select the best vegetation index (NDVI or EVI) to be adopted in the VCI calculation. Three meteorological variables (air temperature, evapotranspiration and rainfall) were used in this analysis for selecting the best vegetation index. Meteorological data were obtained from the stations of INMET and ANA. Equation 3, proposed by Pearson (1982) and Pearson, Fischer and Inman (1994) was used to calculate the correlation.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (3)$$

where
r = Pearson’s correlation coefficient;
$\bar{x}$ = x sample average; and
$\bar{y}$= y sample average.

According to Figueiredo Filho and Silva Júnior (2009), Pearson's correlation coefficient (r) can present both negative and positive correlations with a range of values between -1 and 1. The closer to one, greater the linear association between variance of the indexes used and the closer to zero, lower this association. If the correlation is negative, the association will be inverse (Table 3).

Table 3 - Classification of Pearson's correlation coefficient

PEARSON’S COEFFICIENT (r)	CORRELATION
r = 1	Perfectly positive
0,8 ≤ r < 1	Strongly positive
0,5 ≤ r < 0,8	Moderately positive
0,1 ≤ r < 0,5	Weakly positive
0 ≤ r < 0,1	Minimally positive
0	Null
-0,1 ≤ r < 0	Minimally negative
-0,5 ≤ r < -0,1	Weakly negative
-0,8 ≤ r < -0,5	Moderately negative
-1 ≤ r < -0,8	Strongly negative
r = -1	Perfectly negative

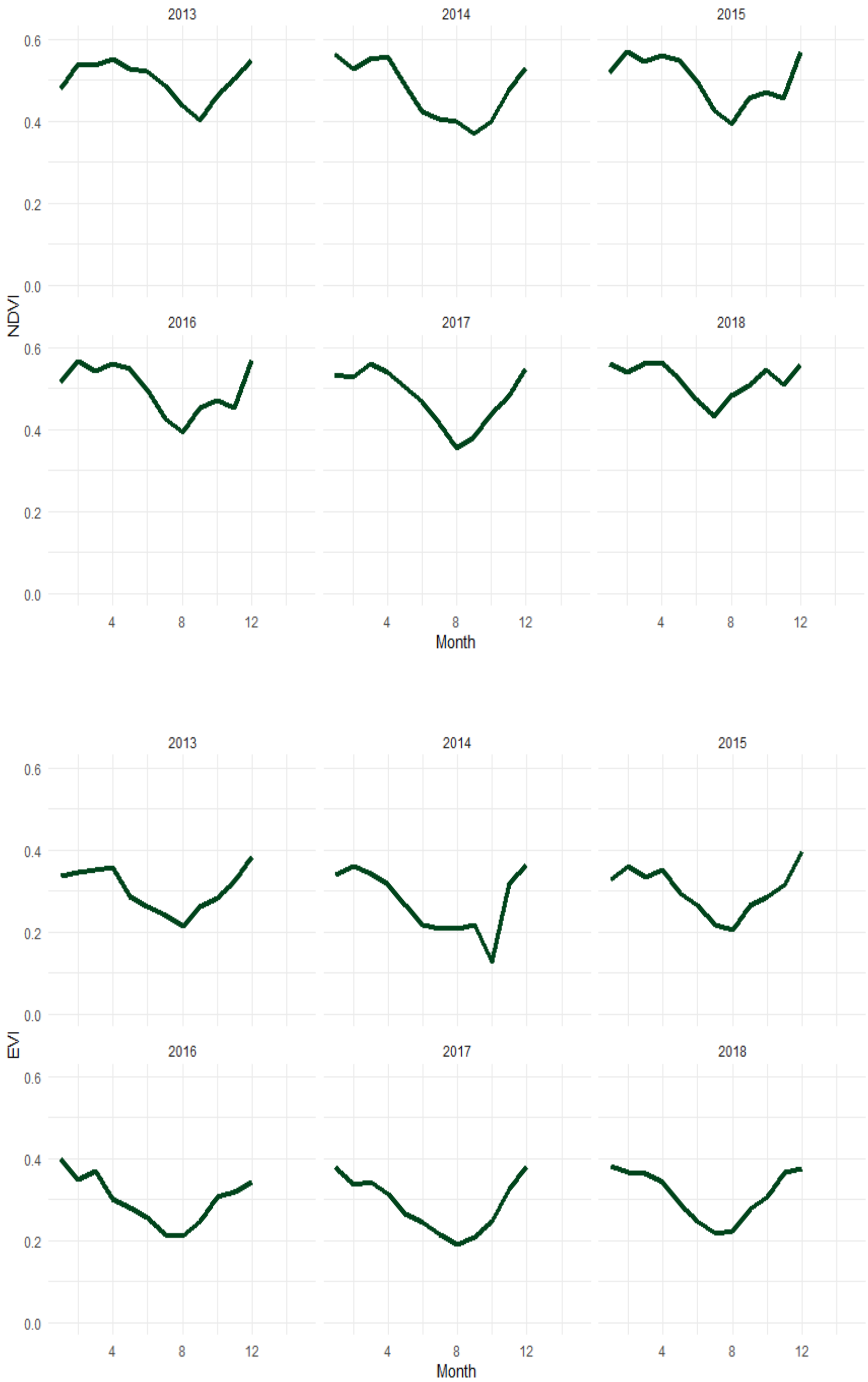
Source: Modified from Cohen (1998); Dancey and Reidy (2006) and Paranhos et al. (2014).

RESULTS AND DISCUSSIONS

Best vegetation index selection for drought analysis using Cox-Stuart Test

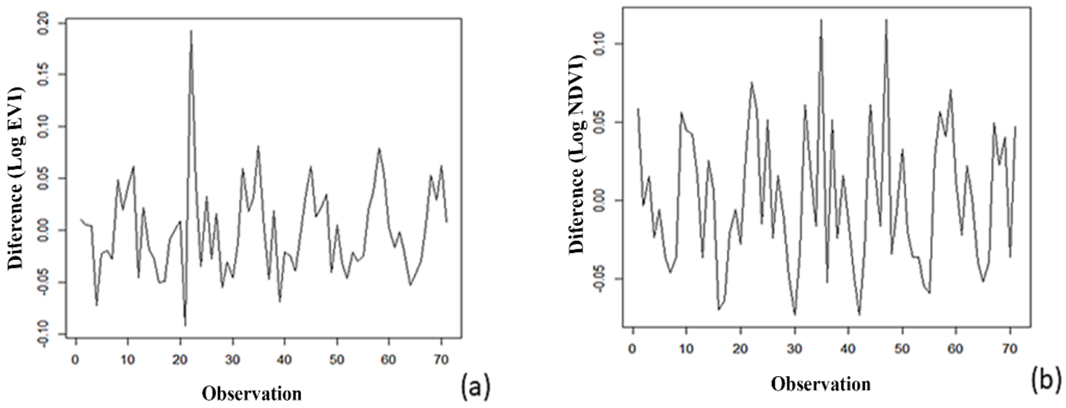
The analysis of time series data showed the presence of seasonality patterns over the time. It was possible to observe peaks of greater vegetative vigor and moments of fall in values, caused by dry periods (Figure 5). According to Chaves, Mataveli and Justino (2014), this variation is directly associated with precipitation, since the beginning of rains contributes to the increase of vegetative vigor in a region.

Figure 5 - Variation of NDVI and EVI in the Serra Azul stream sub-basin for period from 2013 to 2018



Source: The Authors.

Figure 6 - Difference of transformed series from Cox-Stuart Test, (a) EVI and (b) NDVI



Source: The Authors.

Through the analysis of difference between pairs of variables obtained from stationary series transformed from original vegetation index data, it was identified that NDVI registered a greater tendency to present seasonality patterns in comparison with EVI data (Figure 6). Furthermore, it was observed that NDVI data showed less variation between their intervals compared to EVI data.

The hypothesis results (Table 4) demonstrated that when p-value is greater than 0.05, in a 95% confidence interval, there is no statistical evidence to reject the hypothesis. That is, the EVI values of time series did not show seasonality, whereas in NDVI data, the presence of seasonality was identified, as p-value presented values below 0.05. In this case, the null hypothesis was rejected. According to Chaves, Mataveli and Justino (2014) and Gow et al. (2016), rejecting Ho hypothesis means that variation in vegetation behavior does not change substantially, indicating that there is a linearity of vegetative vigor present in region.

Table 4 - Analysis of hypotheses of Cox-Stuart test for vegetation indexes obtained from MODIS sensor

	EVI	NDVI
N. of observations	36	36
P-value	0.50	0.01
Sample size	72	72

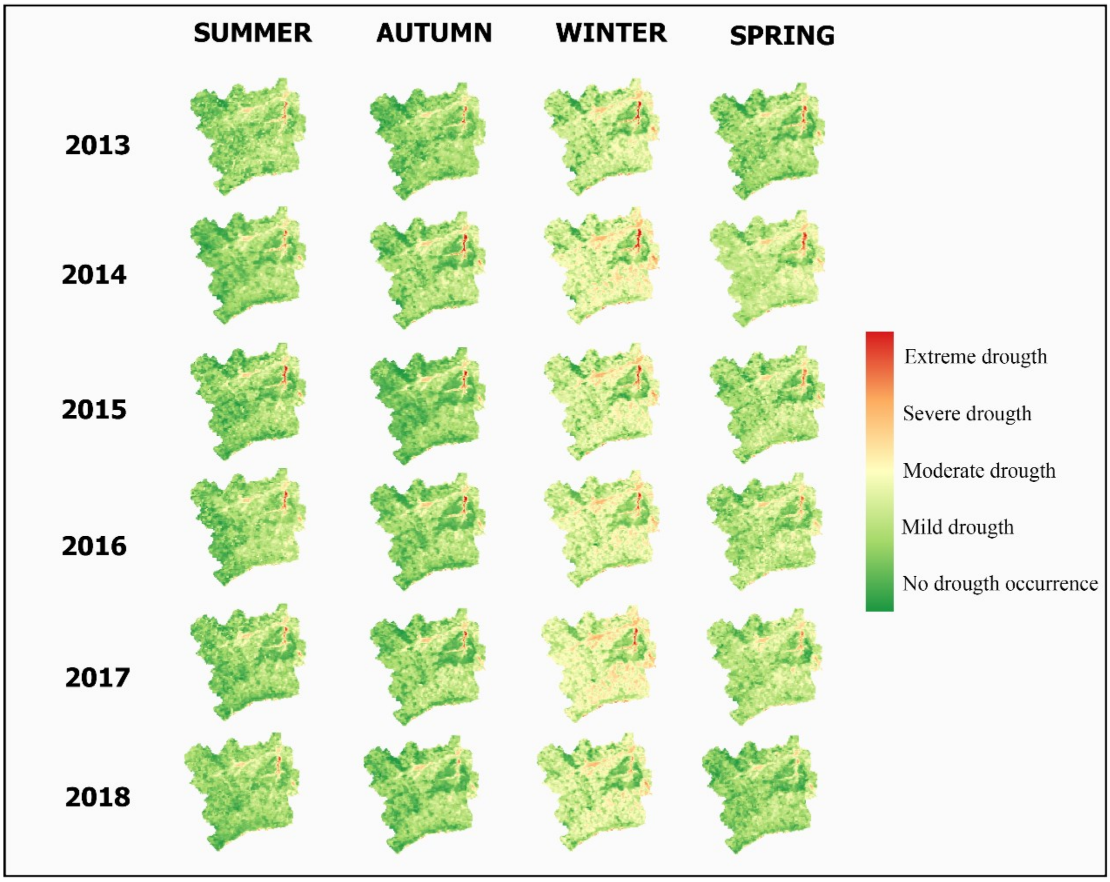
Source: The Authors.

In regions of lower vegetation density, such as transitions from rural to urban space, NDVI is more sensitive to seasonality. This fact occurs because in areas with intense modification of land use, the vegetative vigor has a low saturation in response to the increase in biomass, thus NDVI tends to present a better spectral response in these types of areas when compared to EVI (HUETE et al., 2002). Studies by Nora and Santos (2010) applied to areas characterized by anthropic changes, demonstrate that NDVI tends to present greater variability in relation to sensitivity of canopy changes when compared to EVI. This relationship was demonstrated by Branco (2016) where, contrary to results of present study, the EVI from MODIS sensor data presented the best performance. The main reason for these differences in results is because the region analyzed by Branco (2016) presents a lesser anthropic intervention, mainly because the object of study area corresponds to a biological reserve.

Analysis of drought in study area from NDVI time series

In the researches carried out by Cunha et al. (2017) and Leivas et al. (2014), in Brazilian territorial areas, it was evident that VCI can be used as an important indicator for analyzing different aspects of drought in tropical regions. This index is capable of exploring different water stress conditions in several types of landscapes. The results of vegetation condition index in the Serra Azul stream region enabled to identify the presence of seasonality over the time, distributed over the analyzed VCI classes (Figure 7). In drought months (winter and autumn) this drought was more intense in anthropized areas and in areas adjacent to Serra Azul reservoir, due to lower vegetation cover present.

Figure 7 - Variation of drought classes along time series based on VCI

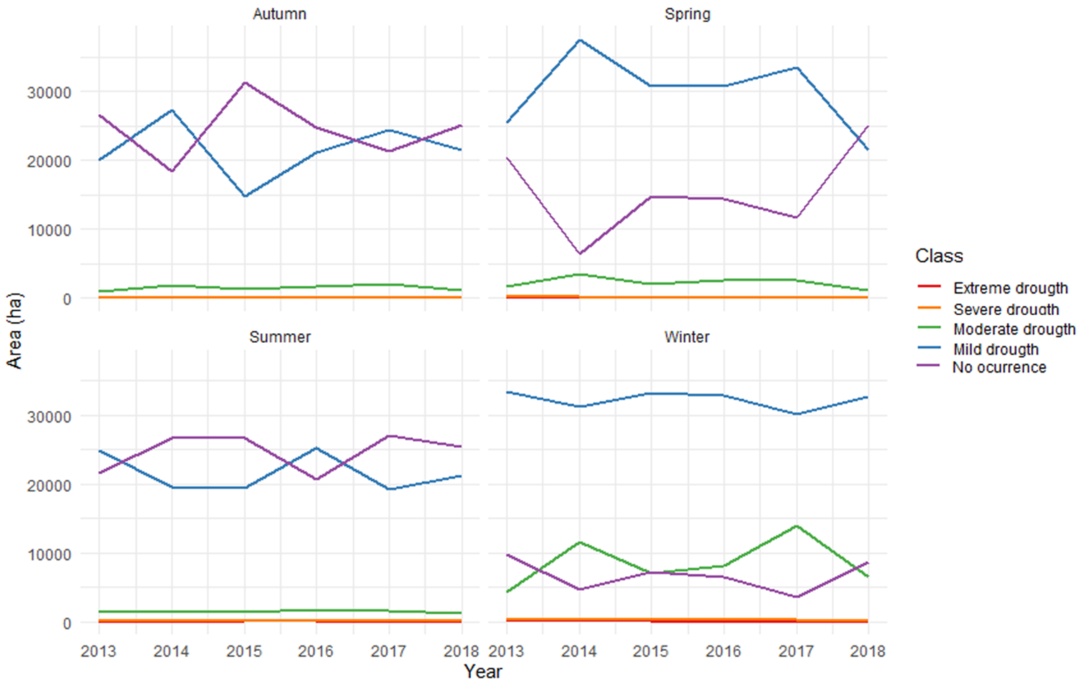


Source: The Authors.

The class of Severe Drought showed a percentage lower than 1% in all seasons analyzed. The Extreme Drought class had largest extensions in years 2014 and 2015 in study region. This class of drought was also found in other regions in years 2014 to 2016, as shown by studies of Uttaruk and Laosuwan (2017) who related a reduction in VCI to an increase in extent of drought areas in a given region.

Most of study region showed VCI values in No Drought or Mild Drought classes (Figure 8). The areas in Extreme Drought class, with VCI values less than 20%, appeared in summer season, between 2014 and 2016, coinciding with period of water crisis that occurred in sub-basin, reported in Minas Gerais (2015), mainly in areas close to water supply reservoir. The spring season showed regions of Extreme Drought class only in years 2013 to 2014. In autumn season, the presence of drought areas was identified between 2013 and 2017 and the same situation occurred in winter season.

Figure 8 - Area extensions in ha of drought classes provided by VCI for each season from year 2013 to 2018



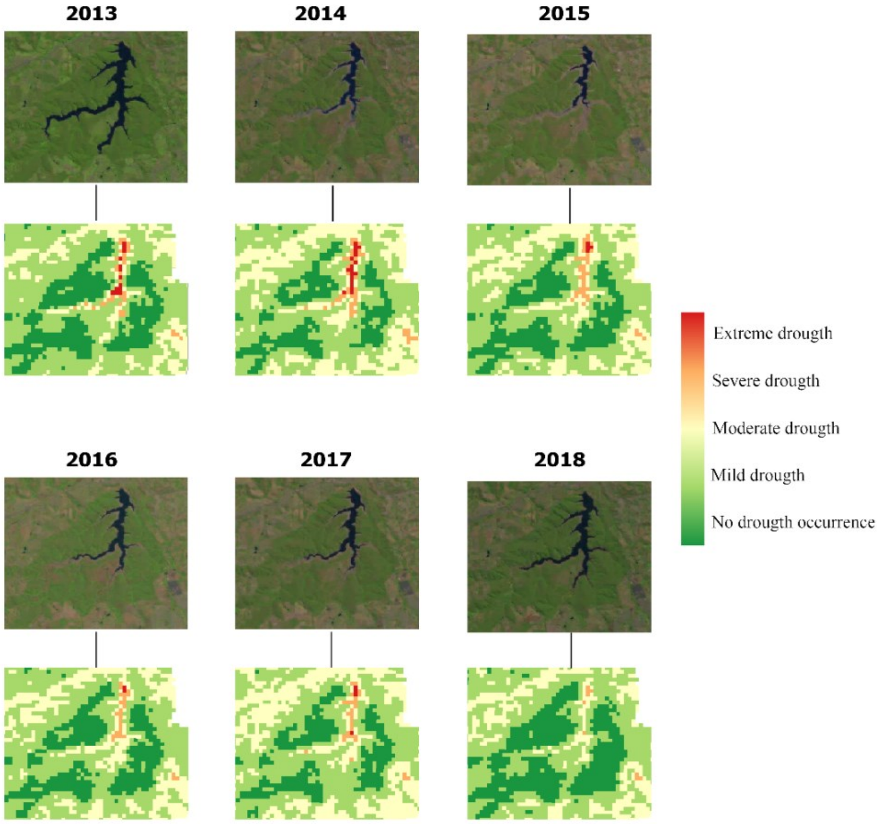
Source: The Authors.

With the application of VCI, it was possible to identify drought variation in the Serra Azul reservoir (Figure 9). According to Florenzano (2013), Formaggio and Sanches (2017) and Ponzoni, Shimabukuro and Kuplich (2015), as the spectral response of water is low in red and infrared bands, in VCI calculation the water regions tend to have a lower value, being associated with regions of Extreme Drought class. In this regard, the results indicated that as areas of Extreme Drought class became more evident, the tendency of water body areas to decrease also increased. As seen in Figure 8, the large concentration of Extreme Drought areas in 2013 favored a decrease in volume of water in reservoir, a fact that was documented for years 2014 and 2015 at the time of water scarcity episode suffered by region (MINAS GERAIS, 2015). In the same way, the increase in areas of Moderate and Mild Drought in reservoir region, between 2016 and 2017, contributed to increase in this area in 2018.

The research shows that changes in land use and natural changes have led to worsening periods of drought in the sub-basin, especially in years of water scarcity, as reported by Minas Gerais (2015). According to Dutra (2021), the influence of land use variations and natural events on the worsening of the drought phenomenon in the study region was identified based on water balance calculations in the sub-basin. In this regard, the changes associated to urban and agricultural expansion in region caused soil impermeability and a consequent decrease of basin maximum storage volume. Thus, in years when there is a decrease of water entry in system, due to movement of air masses that provide low precipitation, the region presented a decrease in water volume and increase of the worsening drought classes. This causes water scarcity episodes and difficulty in supplying water to the population due to the decrease in the Serra Azul reservoir volume.

According to Kamble et al. (2019) and Eyoh, Okeke and Ekpa (2019), Yulistya, Wibowo and Kusratmoko (2019) and Baniya et al. (2019), the variation of VCI classes occurs due to the ability of this index to demonstrate the worst and the best drought condition over a time period due to the variation in precipitation and temperature in the region. The rains have a strong interaction with vegetation, being able to directly influence in vegetative vigor of a region. Thus, the greater the storage of water in vegetation structure, greater the VCI value and less the chance of this vegetation suffering from drought events.

Figure 9 - Classification of VCI for the Serra Azul reservoir region in dry seasons (winter and autumn)



Source: The Authors.

The results obtained allowed to identify drought events extent and influence of seasonality over seasons in the sub-basin through the application of VCI. It was observed that region presented periods of extreme drought, with a worsening between 2014 and 2016, allowing identifying the water scarcity process that occurred in study region since regions of extreme and severe drought were located close to the regions of reservoir and without vegetation presence in region.

Comparative analysis of NDVI, EVI and VCI indexes for drought monitoring in watershed regions

The results indicated that the VCI showed a better correlation with meteorological variables, between moderately and strongly positive, when compared to data of vegetation indexes (Table *5*). This correlation has been corroborated in several international studies such as those of Zambrano et al. (2016) and Gomes et al. (2019), that demonstrated the VCI has a strong correlation with meteorological data, being considered a very useful tool for analysis in regions where there is a worsening drought. According to Xu et al. (2020) and Gu et al. (2019), the normalization of NDVI data in the VCI calculation process contributes to a moderate and strong correlation when compared with meteorological data. Normalization, allows the analysis of drought and seasonal trends presented in a region over the climatic variation.

Table 5 - Pearson's correlation coefficient (r) between indexes and meteorological variables for period from 2013 to 2018.

	NDVI	EVI	VCI
Evapotranspiration	-0.52	-0.35	0.83
Precipitation	0.11	0.28	0.54
Air Temperature	0.23	0.25	0.75

Source: The Authors.

The correlation of vegetation indexes, such as NDVI and EVI is not a straightforward function in relation to climatic variables, so arising discrepancies when correlated. The results of research identified that vegetation indexes presented a correlation between moderate and weak with climatological data. According to Cohen (1998), Dancey and Reidy (2006), Paranhos et al. (2014), Nora and Santos (2010) and Quesada et al. (2017), meteorological variables usually do not show strong correlation values (above 0.8) when compared to vegetation indexes. This is because plant areas only show physiological changes after effective occurrence of a certain environmental phenomenon. The changes are not manifested immediately during the occurrence of the event.

Results showed that EVI is more dependent on precipitation variable while the NDVI is more dependent on temperature. This relationship was corroborated in studies presented by Kafer and Rex (2020) and Nora and Santos (2010), who reported a better correlation between NDVI and air temperature than precipitation due to the fact that forest formations have resistance to short periods of water scarcity. According to Chaves, Mataveli and Justino (2014), as the vegetation develops, the standard deviation of vegetation index data in a time series increases. The lowest values of these variables tend to appear in periods of drought, especially in winter, between August and October, being related to lack of rain, which causes a decrease in values of vegetation indexes.

It was found in the results that VCI has a better interaction with climate data if compared with data on vegetation indexes, such as EVI and NDVI. The normalization of data performed in the process of VCI calculation allows a better identification of seasonal variations and influence of climatic variables on vegetation of a region.

FINAL CONSIDERATIONS

Through the statistical analysis adopted in research methodology, NDVI was identified as a more effective vegetation index than EVI in characterizing drought for transition regions from rural to urban space. The vegetation condition index (VCI) proved to be feasible and suitable for monitoring drought over study period between 2013 and 2018 having effectively delimited states of drought in study area, also making clear association of index with meteorological data. Finally, the widely available data from MODIS sensor that allowed reaching these results have been demonstrated as suitable and effective in characterizing these drought events investigated in study area.

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AUTHORS' CONTRIBUTION

Débora Joana Dutra contributed to the elaboration and consolidation of all phases of the work, assisted by Marcos Antônio Timbó Elmiro. Both authors had an interactive involvement in the phases of writing and organizing the text, in the bibliographic research, in the scientific foundation, in the establishment of methodologies, in software tests, and in the analysis of results. Carlos Wagner Gonçalves Andrade Coelho contributed with reviews and guidance related to data and climatological tests, text review, as well as consistency in discussions and results. Marcelo Antônio Nero and Plínio da Costa Temba contributed with reviews and guidance related to tests and applications of cartography and geoprocessing, as well as map analysis and data consistency.