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Desertification trends in the Northeast of Brazil over the period 2000–2016

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ABSTRACT

Information about changes in land use and land cover is useful to address issues related to drylands management, as well as to support decision-making related to the sustainable use of soils. Since drylands are frequently affected by accelerated soil erosion, land degradation and desertification associated with vegetation cover losses, constant monitoring of land use and land cover changes are required. However, land use and land cover maps are often not available, making it difficult to monitor degradation. Therefore, in this work, we developed an efficient mapping method to monitor bare soil areas, which are indicative of land degradation in the case of the Northeast of Brazil, using Normalized Difference Vegetation Index images. The proposed methodology was field calibrated and applied to the region using 17-year (2000–2016) NDVI maps, with a spatial resolution of 250 m. Based on bare soil mapping, we estimated the degree of degradation using an index calculated from the persistence and frequency of bare soil during the study period. The results indicated that the degraded areas increased in the period of the study, mainly in areas of pasture and *Caatinga*. This expansion has been accelerated due to the severe drought that affected the region since 2011.

1. Introduction

After five centuries of disordered occupation, the Brazilian semiarid have been degraded by inadequate land management, such as slash and burning agriculture, overgrazing and overexploitation of woody resources as a fuel source (Menezes et al., 2012; Vieira et al., 2015).

The natural vegetation that dominates the Brazilian semiarid region is a savanna-steppe known as *Caatinga*. *Caatinga* vegetation has a high spatial variability, both floristically and physionomically (Andrade-Lima, 1981), mainly determined by the amount and seasonality of rainfall. Physiognomic types are locally denominated shrubby, woody, shrubby/woody and park (Araújo et al., 2007), and can reach heights of up to 20 m. It is very difficult to determine how much of the variability is due to differences in other local physical conditions, for example soil type, or to human interference, since the semiarid zone of Brazil has been inhabited for more than 10,000 years (Sampaio, 1995). *Caatinga* vegetation is rich in therophyte species, which remain as seeds in the soil during the unfavorable season, vegetating only in the rainy period. The woody species, classified as phanerophytes and chamaephytes, typically shed their leaves during the dry season (Costa et al., 2007).

In addition, traditional agricultural practices involve slash-and-burn and shifting cultivation. Burning of the vegetation occurrs by the end of the dry season, when the wood debris lost most of their humidity (Mamede and Araújo, 2008). Such fallow-farming system have converted Caatinga vegetation in a mosaic of regenerating forest patches with different ages (Sobrinho et al., 2016).

Based on data of secondary growth of the *Caatinga* vegetation, Araújo Filho (2013) concluded that the fallow time of agricultural land should be 40 years, but the anthropic pressure has reduced this period to ten years and even shorter periods, not giving sufficient time for the recovery of the soil and vegetation. It is important to mention that the region is considered to be the Brazilian ecosystem most vulnerable to climate change due to the reduction of rainfall deficit and increased aridity over the next century (Marengo et al., 2016).

Previous studies (Helldén, 2008) recognized that areas with bare soil over a long period of time are a good proxy of desertification since they are more vulnerable to degradation considering that unprotected topsoils are susceptible to severe erosion (Hill et al., 1995). Araújo Filho (2013) showed that it is mainly the *Caatinga* areas of bare luvisols and argisols, which cover 25%–64% of the whole area, that are generally exposed to high rates of soil erosion. It was estimated that the whole region has annual soil losses of approximately 50 t ha^{-1} (Araújo Filho,

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2013).

Remote sensing products have frequently been used in land degradation studies since the 1980s (Tripathy et al., 1996; Schmidt and Karnieli, 2000; Maldonado et al., 2002; Zhang et al., 2008; Nkonya et al., 2011; UNEP, 2012; Fensholt et al., 2013; Dardel et al., 2014, among others). On a global scale, one of the most common indicators in the assessment of degradation / desertification are the vegetation indices derived from satellite images, such as the Normalized Difference Vegetation Index – NDVI. This is the most frequently used index by the United Nations Convention to Combat Desertification - UNCCD (UN, 2001). Multi-temporal analysis of NDVI data allows the detection of desertification trends based on the relationship between NDVI and vegetation greenness and cover (Zhang et al., 2008; Purkis and Klemas, 2011; Dardel et al., 2014; Higginbottom and Symeonakis, 2014). In areas where biomass productivity is lower, NDVI values tend to be lower, indicating a larger proportion of bare soil surface (Nicholson and Farrar, 1994; Bai et al., 2008).

Together with the identification of bare soil, the characterization of the different tree strata and biomass has also been used as an indicator of the degree of desertification (Le Houerou, 2006; Barbero-Sierra et al., 2015; Torres et al., 2016). According to Zhang et al. (2016), areas with tree and shrub coverage greater than 50%, or where there is more than 70% forage coverage of the surface, are less susceptible to soil degradation process.

Because the Brazilian *Caatinga* is a complex ecosystem with a large variety of trees, shrubs and pastures that are unequally distributed, with highly fragmented landscape due to several anthropic land uses, it produces a wide range of spectral responses. Consequently, to determine the threshold responses of bare soil, we related NDVI values to a biomass index used extensively in local field surveys. Using this relationship, we determined threshold NDVI values correspondent to bare soil areas and mapped areas without vegetation for the period of 2000–2016.

It is important to note that severe droughts, deforestation for firewood production, and the slash and burning agriculture result in very low values of NDVI, similar to those of bare soil, that recover with the return of regular rainfall. Unless regenerated patches, degraded areas show little or no signs of re-greening in the wet season. Therefore, we proposed a degradation index based on the frequency and persistence of bare soil, which was used to characterize the degradation/desertification extension and intensity during the study period.

2. Materials and methods

2.1. Study site

With an extension of approximately 1 797 123 km^2, approximately 20% of the total Brazilian territory, the study area is located in the equatorial zone (1–21 °S, 32–49 °W, Fig. 1). The region is characterized by intense solar radiation, low cloudiness and relative humidity, high potential evapotranspiration, rainfall that ranges from less than 800 mm y^{-1} within the semi-arid region to more than 1500 mm y^{-1} in the rainy zone along the eastern coast, precipitation concentrated over 2–5 months during the wet season, and a high degree of spatial and temporal variability (Cunha et al., 2015). A large fraction of the area (approximately 982 563 km^2) is classified as semiarid climate (Alvares et al., 2013).

2.2. NDVI data

In this work, we used 1552 MODIS images from the Earth satellite, available at http://modis.gsfc.nasa.gov/, with a spatial resolution of 250 m, corresponding to the four tiles that encompass the study area (h13v9, h14v9, h13v10, and h14v10) for 388 imaging dates from 2000 through 2016. The product used was MOD13Q1, which is the NDVI vegetation index produced every 16 days, which has been corrected for atmospheric effects. NDVI is a quantitative measurement based on vegetation spectral properties and related to biomass and vegetation vigor. It is indicative of plant photosynthetic activity related to leaf area index and the fraction of PAR absorbed by vegetation. For this reason, high values of NDVI identified healthy vegetation, while low values are associated with stressed or diseased vegetation. The index is obtained through the relationship between the reflectance (ρ) of the near infrared (IVP) and red (V) bands using the following equation:

$$NDVI = \frac{\rho IVP - \rho V}{\rho IVP + \rho V} \quad (1)$$

2.3. Defining wet and dry seasons and estimating NDVI annual means

Several studies have shown that vegetation responds to climate variability (Zhou et al., 2014). Consequently, NDVI values present subtle temporal variations on large scales, making it difficult to interpret the results of this type of study (Bégué et al., 2011). Thus, to interpret NDVI trends due to changes in land use and land cover, rainfall variability, which is the main factor of the NDVI variation, has been considered (Hickler et al., 2005).

Rainfall in the Brazilian semiarid region shows high spatial and temporal variability (Marengo et al., 2016), split over 3–4 months of the wet season, followed by a long dry season during the remainder of the year. We determined the onset and demise of the wet and dry seasons based on the analysis performed by Cunha et al. (2015). Using data of 1974 meteorological stations for the period 1970–2012, they identified the months of the year with a high frequency of rainy days and divided the area into five regions, which are entirely consistent with the different rainfall regimes of the study area described by Kousky (1979). For the purpose of this study, we treated the remaining months as the dry season, excluding a two-month interval prior to the onset and the end of the wet season to minimize potential interferences in the NDVI values associated with inter-annual shifts in the wet season onset/demise.

Considering the months corresponding to each season, the average NDVI values were calculated for each season, resulting in two images for each year. Thus, the original dataset was reduced to 34 images, referring to the mean values of NDVI for the dry and humid season of the 17 year-period analyzed.

2.4. Calibration of NDVI values for bare soil

The spatial variability of soil and plant reflectance requires extensive in situ measurements, which is not feasible in most studies (Montandon and Small, 2008). Thus, due to the extension of the study area, field analyses were conducted in an eastern region of the study area from September 11 to 16, 2016, in an area of approximately 4908.20 km^2. The region is known as Alto Sertão Sergipano, is located between the coordinates 9°30′S to 11°30′S and 36° 'W to 38°30′W and is one of the priority areas of the United Nations Development Program - UNDP for recovery from degradation. The period chosen for conducting field evaluations was the dry season because it was the most favorable time to map *Caatinga* vegetation (Guimarães, 2009; Lopes et al., 2010; Chaves et al., 2012). The field data sampling technique used was non-random (selective): we collected 170 ground-truth points, with large extensions of bare soil and different degrees of vegetation density, pasture and agriculture, to serve as training samples for the classification of a wide range of NDVI values. Using Landsat 8 images, we drew polygons around each point and assigned the polygon to a land use and land cover class (bare soil, pasture, agriculture and forest). In order to determine the degradation history of each field point, we applied questionnaires to the local community to verify for how long the area remained as bare soil. Training samples (number of locations and number of pixels) were then associated to the NDVI range for bare soil classification.

Fig. 1. Map of Brazil showing the study area (shaded in brown), with the different vegetation types that occurred in the area.

To calibrate the threshold value of NDVI (continuous quantitative value) for bare soil, both for the dry and wet seasons, it was necessary to compare the range of NDVI values for the different vegetation or land uses inspected in the field (qualitative attribute).

Caatinga vegetation has a complex herbaceous and arboreal structure, which makes it difficult to discriminate height and vegetation density. For this reason, it is necessary to use a methodology for labeling landscape attributes with different vegetation cover and then generate quantitative values that can be correlated with the values of NDVI. In this study, we used the methodology developed by Chaves et al. (2008), extensively applied in several previous studies (for instance Oliveira et al., 2009; Guimarães, 2009; and Francisco, 2013) to characterize *Caatinga* vegetation, which is based on a Woody Vegetation Biomass Index – *WVBI*, calculated by combining a Height Index – *HI* and a Cover Index - *CI*. The height index ranges from 0 to 1 and is defined according to morphological features of the vegetation communities, as indicated in Table 1. The cover index is estimated considering the density of vegetative coverage, indicated in Table 2, and ranges from 0 (less dense) to 1 (denser).

For homogeneous areas, WVBI is estimated as follows:

$$WVBI = HI\ CI \tag{2}$$

For composite classes with vegetation of more than one height, the WVBI is determined by weighing, according to predominance of each of the vegetation heights described: weight 3 is assigned as the weighting factor of the first component of the composite class, defined by Table 1; weight 2 for the second, and 1 for the third:

$$WVBI = \frac{3HI_1 + 2HI_2 + HI_3}{6} CI \tag{3}$$

where the sub-indices 1–3 indicate the vegetation classes of the group.

Table 1
Height Index – *HI* used to classify *Caatinga* vegetation types.

Vegetation class	Height (m)	*HI*
Arboreal	> 4.5	1
Sub arboreal	3.0–4.5	0.75
Shrubland	1.5–3.0	0.5
Sub shrubland	< 1.5	0.25
Bare soil		0

Table 2
Cover Index - *CI* determination according to the surface coverage.

Subclass	Surface Coverage (%)	*CI*
Very dense	> 80	1
Dense	60–80	0.80
Open	40–60	0.60
Sparse	20–40	0.40
Very sparse		0.20
Without vegetation		0

All the field points visited were classified, having the value of *WVBI* calculated, as well as the NDVI value of the corresponding pixel. Using this basic information, the threshold NDVI values for bare soil were defined as follows:

- Field data were ordered by the increasing values of NDVI and the correspondent *WVBI* values, a segmentation of classes was done according to the most representative Caatinga vegetation types, and the correspondent interval of values of *WVBI* for each class were determined;
- based on the pair *WVBI* and NDVI values, a linear relationship among both indices was calculated;
- subsequently, the theoretical limit values of NDVI for the *WVBI* classes were estimated using the linear regression equation; and
- finally, NDVI threshold values for bare soil for both the wet and dry seasons were determined.

Once the maximum values of the NDVI for bare soil, for both the dry and wet seasons, were defined, new images were generated for each of the 17 years analyzed. For each image, a conditional operator based on the following rule was applied: the pixel was rated 1 when the average value of NDVI was less than or equal to bare soil thresholds of both the wet and dry seasons; otherwise, the value 0 was assigned to the pixel. Thus, every pixel of the image has a value of 1 in the presence of bare soil in both the dry and wet seasons and otherwise has a value of 0.

Since *WVBI* index value were calculated for Caatinga vegetation only, and exclude anthropic land uses, we also verified if the values of NDVI for those field points located in non-degraded pasture and crop areas were above the NDVI threshold defined for bare soil. The wet season threshold is also important for temporary crops areas where the dry season fallow shows, in some cases, low values of NDVI.

2.5. Degradation index

Field surveys in the *Caatinga* biome (Costa et al., 2002) have shown that areas under severe degradation are associated with low biomass and consequently with low values of NDVI.

Because of the high inter-annual and intra-seasonal variability of rainfall, frequent droughts and dry spells occur in the semiarid Northeast. In response to this variability, the Brazilian *Caatinga* exhibits large variations in vegetation greenness, coverage and tree mortality, both in space and time, which are directly reflected in the NDVI values. In addition to this, the use of woody vegetation as energy sources in many areas of the region and the common land management practice among poor farmers of slash-and-burn agriculture causes complex spectral responses that vary from year to year.

Therefore, the definition of degradation used in this paper was based on the frequency and persistence of bare soil for a period of time long enough to avoid temporary effects, such as denudation associated with episodic droughts and dry spells and anthropogenic land uses. Unlike other studies, which are generally based on imagery for a limited number of dates (Zhang et al., 2008; Dawelbait and Morari, 2012; CGEE, 2016), we are proposing a degradation index that includes information about the history of vegetation cover, which is given by

$$DI\,(YEAR_1 - YEAR_n) = \sum_{i=1}^{n} w_i BS_i \tag{4}$$

where DI indicates the degradation index between the first and the last year analyzed, indicated by $YEAR_1$ and $YEAR_n$, respectively; BS is a dichotomous variable defined by the NDVI threshold values for bare soil, as explained before; w_i is a weight factor for the year i; and n is the number of years of the period analyzed.

The weight w_i determines the relative importance of the presence of bare soil of a particular year in the calculation of the degradation index. In this study, the weight factor was assumed to vary linearly between the first and the last year of the period analyzed according to

$$w_i = \frac{2(1-r)}{n(n-1)(1+r)}\,(YEAR_i - YEAR_1) + \frac{2r}{n(1+r)} \tag{5}$$

where w_i is the weight correspondent to $YEAR_i$, while $YEAR_1$ if the first year of the period analyzed; and r is the ratio of the weight attributed to the first year and the last year of the series analyzed, thus, $r = w_1/w_n$. The value of r can vary between 0, which indicates that the bare soil of the first year analyzed has no influence on the composition of the degradation index, and 1, which indicates that the bare soil data of all the years of the series analyzed have exactly the same weight.

Since the sum of the values of the weights defined by Eq. (5) for the whole period analyzed always equals 1, the degradation index *DI*, defined by Eq. (4), varies between 0 and 1. When the pixels have no bare soils for the whole period analyzed, *DI* is equal to 0. On the other hand, when *DI* equals 1, this indicates that the pixel remained bare soil for the whole period.

Considering that the dichotomous variable *BS* is determined by the NDVI threshold values for bare soil, it was necessary to assume the values of *n* and *r* in Eqs. (4) and (5). In addition, after calculating the degradation index, it was necessary to determine the intervals of *DI* values that define the degrees of degradation, which were moderate, high and very high in this study. To adopt the best values, we used the field evidence collected in this study along with other sources of data that studied and identified degraded areas in the whole region (MMA, 2007).

In addition, we compared the degradation coefficient derived using Eqs. (4) and (5) against detailed aboveground biomass estimations from the Seridó priority area of 5516 km^2 from Accioly et al. (2008), which is located to the north of our study area and has a long history of desertification. Accioly et al (2008) conducted field studies to derive a relationship between the area plant index and aboveground biomass, deriving the spatial distribution of biomass by relating the area plant index to NDVI values extracted from Landsat images from 2000 and 2001. Accioly et al (2008) concluded that those areas with aboveground biomass below 5 Mg ha^{-1} were under severe desertification.

It is important to mention that polygons classified as urban areas, rock outcrops and water bodies, such as rivers and reservoirs, were excluded in the degradation mapping. Since those areas are associated with low NDVI values, pixels belonging to those classes could have been erroneously classified as bare soil and included in the degradation calculations. This information was extracted from Vieira et al. (2015).

3. Results

3.1. Annual mean NDVI values for the wet and dry seasons

Fig. 2 shows the five regions delimited in the Northeast of Brazil based on the analysis of the frequency of rainy days performed by Cunha et al. (2015) and combined with the definitions of the dry season used in this study. In general, the different regions are in agreement with the rainfall regimes defined in previous studies (Kousky, 1979) and simply reflect the meteorological system responsible for precipitation in the area. It is clear that the contrasting rainfall regimes in the area made it necessary to perform NDVI calculations during different times of the year in each region.

Based on the climatic regime regionalization defined in Fig. 2, we identified the sites of the study area with bare soil that were free of vegetation, both in the wet season and in the dry season. Fig. 3 shows that NDVI values are lower in the dry season, especially in those areas dominated by Caatinga vegetation, since this type of vegetation loses its leaves at the beginning of the dry period. Lower values of NDVI were also observed on the western edge of the study area in both seasons. This region is considered a large agricultural frontier and the country responsible for much of Brazil's grain and fiber production. Thus, because this region has extensive agricultural areas, the soil is uncovered

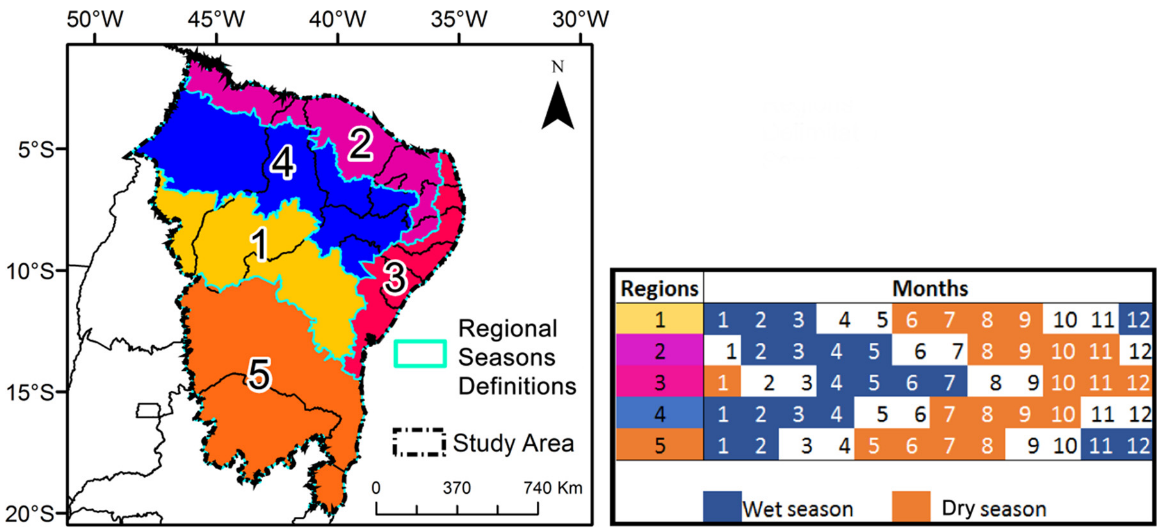


Fig. 2. Wet and dry season definition in the study area.

in the wet season due to soil preparation and in the dry season since the harvest occurs at the beginning of the dry season. In addition, approximately 20% of this area presents sandy soils (Lumbreras et al., 2015) that have a higher reflectance and consequently have a strong influence on the NDVI values (Huete et al., 1985).

3.2. Calibration of threshold of NDVI for bare soil

Fig. 4 shows the NDVI values for each field point in ascending order and their corresponding *WVBI* values determined in situ, where we can highlight three different intervals:

- Range 1: NDVI values ranging from 0 to 0.30, mostly composed of bare soil and herbaceous-graminoid vegetation and a very low density of subshrubs. The average value of the *WVBI* was 0.008.
- Range 2: NDVI ranging from 0.30 to 0.40. This is a transition interval, with vegetation types varying from herbaceous-graminoids and crops to areas with sparse, arboreal vegetation. The average value of *WVBI* was 0.145.
- Range 3: NDVI values greater than 0.40. The presence of dense vegetation, from very dense subshrub/shrub vegetation to very dense trees. The average value of *WVBI* was 0.768.

The linear regression analysis between the *WVBI* and NDVI values for the field points resulted in a correlation coefficient value, R^2, of 0.78 (Fig. 5). Although other spectral indices were tested, namely, the reflectance of the red visible band – SAVI and the reflectance of the near infrared band – EVI (data not shown), the NDVI showed the best correlation with *WVBI*. In addition, the NDVI had a greater amplitude in relation to the range of the reference values of *WVBI* (more sensibility), allowing a better discrimination of threshold values of vegetation classes. Besides differentiating Caatinga vegetation physiognomies from bare soil, Fig. 4 allows to determine NDVI threshold values that separates natural vegetation from degraded areas.

Based on vegetation types found in the field, categorical classes were defined and the respective *WVBI* and NDVI intervals were determined (Table 3) for the main types of Caatinga vegetation. Although Table 3 indicates that bare soil has values of NDVI less than 0.254, due to the spatial resolution of the image, the maximum value of NDVI stipulated for the class of bare soil also included the presence of very sparse subshrub and shrub vegetation with a cover index of less than 20%. Therefore, pixels with an NDVI value of less than 0.3 in the dry

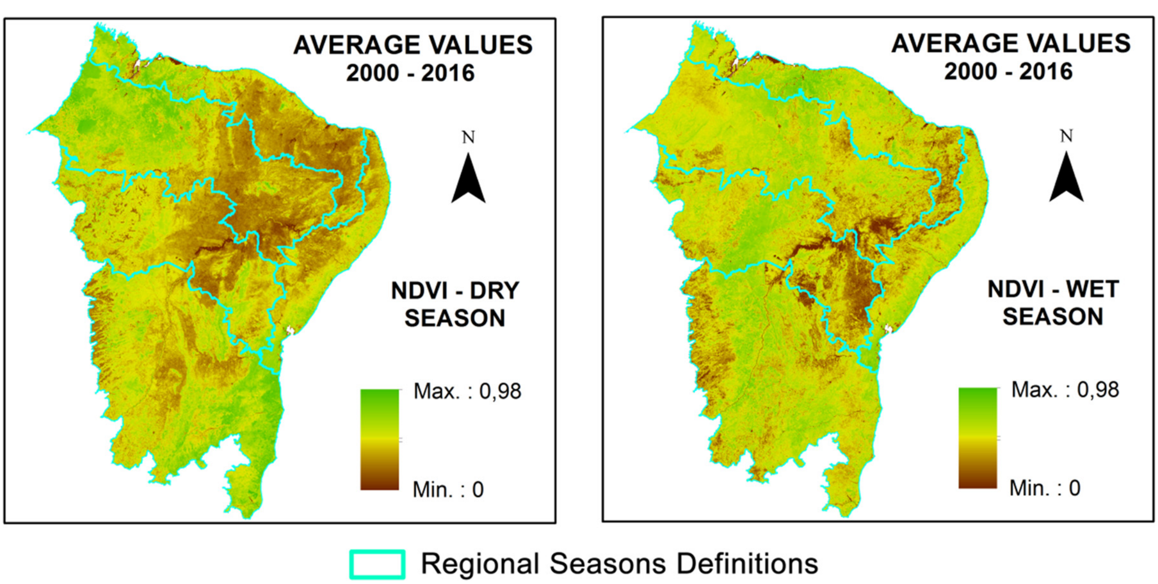


Fig. 3. Average NDVI values for dry (left) and wet (right) seasons.

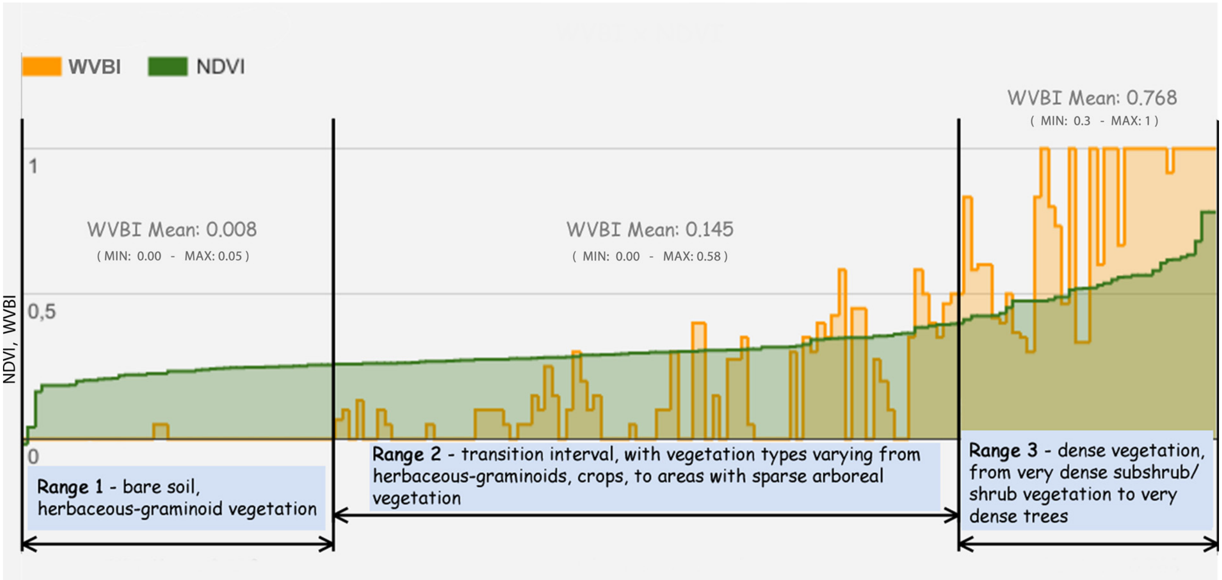


Fig. 4. Values of NDVI in increasing order and their correspondent *WVBI* values for 174 field points surveyed.

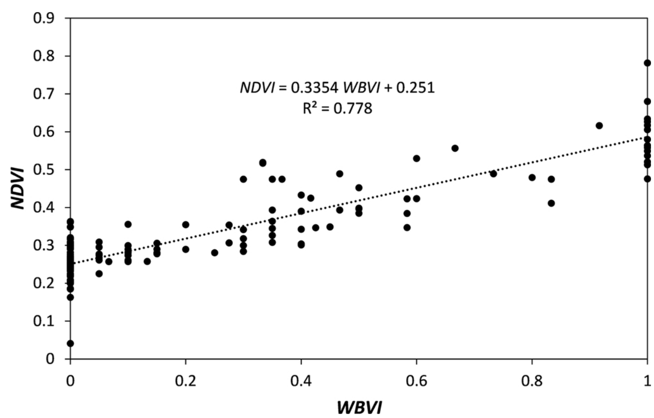


Fig. 5. Relationship between the Woody Vegetation Biomass Index and NDVI in 174 field points surveyed in the study area.

Table 3
Caatinga main vegetation types and the correspondent Woody Vegetation Biomass Index – *WVBI* and NDVI interval values.

Vegetation types	*WVBI*	NDVI
Very dense Arboreal	0.919–1.000	≥ 0.617
Dense Arboreal / Sub arboreal	0.600–0.919	0.484–0.617
Very dense Shrubland / Sub shrubland	0.460–0.600	0.425–0.484
Open Shrubland / Sub arboreal	0.150–0.460	0.296–0.425
Very sparse Sub shrubland / Shrubland	0.050–0.150	0.254–0.296
Bare soil / Herbaceous graminoids	0	0–0.254

season were classified as bare soil. In addition, it was verified that the same pixels, corresponding to bare soil, have an average NDVI value of less than or equal to 0.55 during the wet season, which was the threshold NDVI value used during the wet period. Although simple, it is clear that the methodology used in this study to characterize the Caatinga was able to discriminate the NDVI response patterns, especially in relation to bare soil identification.

The threshold value for bare soil identified in this study is close to the results of Montandon and Small (2008), which concluded that the best NDVI interval to separate bare soil is between 0 to 0.40, based on 2906 soil samples (wet and dry), while the range of 0.20 to 0.21 is the best to identify soil in dry samples.

3.3. Degradation mapping

As mentioned before, in order to derive the degradation index estimated by Eq. (4), it is necessary to assume values for n, which defines the length of the period of analysis, and for r, which indicates the relative weight attributed to the first and last year analyzed in Eq. (5).

In the case of n, the value adopted was ten years. This value is sufficiently great to include the most exceptional droughts, which last for 4–5 years (Brito et al., 2017), and it coincides with the ten-year period that is equivalent to the fallow time of agricultural land, as estimated by Araújo Filho (2013). In addition, it is in agreement with the cutting cycle of 10–15 years, recommended by Riegelhaupt et al. (2010) for the production of firewood since the recovery of vegetation is 80% or more of the original wood stock and reaches the highest value of productivity in that period.

Regarding the value of the coefficient r of Eq. (5) that defines the ratio between the weight of the first year bare soil map and the last year analyzed, we used the value of 0.5, which indicates that the bare soil map of the first year of the series has half the weight compared to the last. Assuming lesser weights in the first years analyzed indicates that the recent history of land uses was considered to be more important than the first years of the series. In other words, if a pixel shows bare soil in the first five years of the series and no bare soil in the last five, the resulting degradation index would be 0.407. Conversely, if in the first five years the pixel shows active vegetation while in the last five years shows degradation, the index should be 0.592. In practical terms, the degradation index is closer to zero in the first case because the land use trajectory is indicating vegetation recovery. In the latter case, on the other hand, the index is higher because the land use trajectory is suggesting increased degradation. Although several attempts were made to find values of r (data not shown), we concluded that the best value was 0.5, as mentioned before.

Once the coefficients of Eqs. (4) and (5) were defined, the degradation period was calculated for ten-year periods starting in 2000. Thus, the index was calculated for the periods 2000–2009, 2001–2010, 2002–2011 and 2007–2016. Based on field information from previous studies, such as priority areas of MMA and the information collected in this study, the values of the degradation index from Eq. (4) were classified as moderate for values when the DI values range from 0.65 to 0.75, high for DI values between 0.75 and 0.85, and very high for DI values greater than 0.85.

Fig. 6 compares the biomass map of Accioly et al (2008) of the

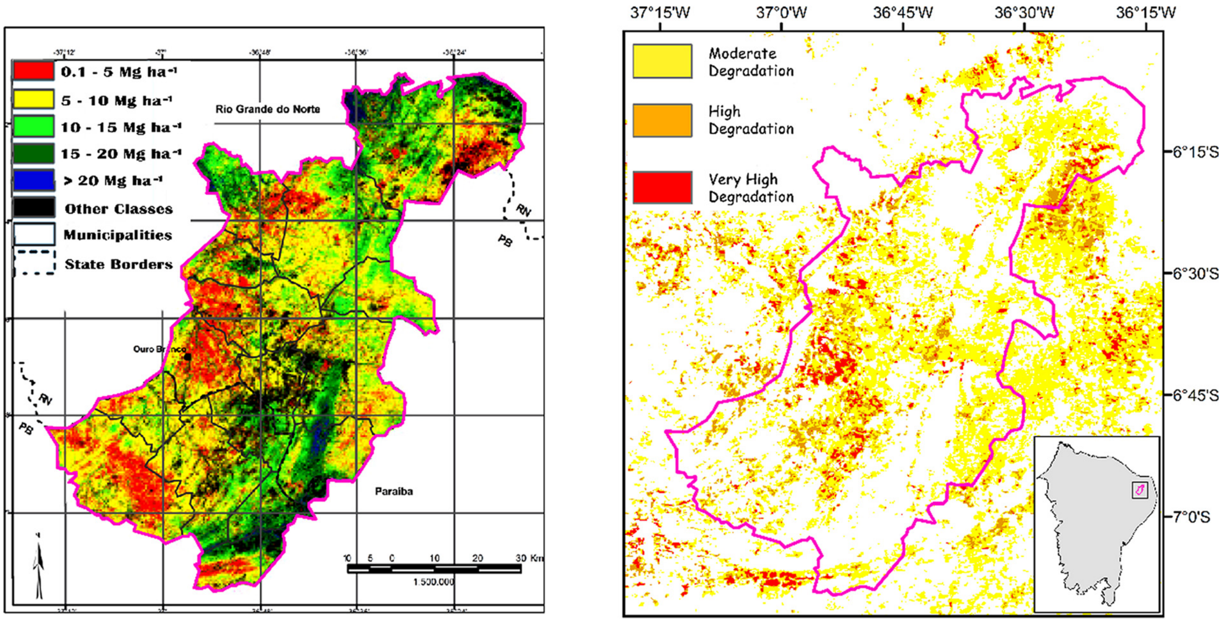


Fig. 6. comparisons between above ground estimations of biomass estimations from Accioly et al (2008) (left panel) for a degraded area of the Brazilian Northeast (inset on the right panel) with the estimations of degradation in this work (right panel).

Seridó priority area, where those areas considered under desertification are colored in red, with our estimations of degradation from Eqs. (4) and (5) for the same site, except for the period of 2007–2016. Despite the limitations imposed by the coarser scale of our study, and the fact that the images used of Accioly et al (2008) portrayed the area conditions in 2000–2001, it is clear that our estimations remarkably captured the spatial distribution of lower aboveground biomass. In quantitative terms, the area estimated by Accioly et al (2008) as desertification (5 Mg ha^{-1}) was 658 km^2, versus 447 km^2 (high and very high degradation) estimated from our study. Most of the discrepancies between both estimations are concentrated in a localized area to the southwest of the study site of Fig. 6, which has been included as desertification in the map of Accioly et al (2008). We analyzed this particular area using recent satellite images and site photographs and observed no sign of generalized degradation, which suggests that this local area might be recovering.

Fig. 7 shows the map of the degradation index generated for the period of 2007–2016, together with the priority areas within the national plan to combat desertification identified by MMA (SAP, 2017). In general, it is possible to observe that areas with high and very high degradation are concentrated in the center of the study area, which coincides with the priority areas to combat desertification.

To the north of the study area, there is also evidence of several hotspots of desertification, which are generally concomitant with MMA priority areas. There are several areas, however, classified as highly and very highly degraded in this study that are not included in the government´s priority areas that might require further attention.

Fig. 7 also shows desertification priority areas located to the west and south of the study area that show little signs of degradation, with the exception of the Gilbués (#8), a well-known degraded area (MMA, 2007). Those areas were included in the program to combat desertification after 2010, since their history of degradation is relatively recent and, consequently, does not meet the criteria adopted in this study. To the east of the region, however, priority areas have a long history of disturbance and therefore, most of those areas were classified as very high degradation in this study.

Fig. 8 presents the time-evolution of the degradation index for the three categories used in the period of 2000–2016. In general, there is a positive trend (expansion) in areas considered degraded in the whole region, beginning in the period of 2003–2012. A severe and persistent drought has been recorded in the region in the period of 2011–2016, being the most intense in the center of the region (Brito et al., 2017). This suggests an association between the severe drought of the last five years, where the frequency, severity and area affected increased compared to past decades (Brito et al., 2017) and the expansion of areas classified as degraded in this study. Despite all categories of degradation being used in this study showing positive increased trends, the rate is more pronounced in the case of the moderate degraded areas, which suggests that the drought of 2011–2016 is playing a crucial role in those changes. Although desertification does not always result from drought, it can be the product of contingent factors (intended and unintended; human induced and climatic). There are numerous climate-related and biological feedback loops between climate change, drought and desertification (Stringer et al., 2009). Since wider fluctuations in rainfall occurring over the years and decades result in insufficient moisture for vegetation growth, severe drought events can be considered a driver of desertification (Stringer et al., 2009). Several areas of the region have experienced increases in firewood production since 2000 (CGEE, 2016), which is generally associated with increased deforestation rates. In addition, reforestation using exotic species such as eucalyptus and algarroba (Prosopis juliflora), which are relatively successful in terms of survival and growth in normal years, have not withstood extraordinary droughts (Riegelhaupt and Pareyn, 2010). Under severe drought conditions, where biomass growth rates of woody vegetation decrease dramatically, the expansion of bare soil areas is an immediate consequence. Moreover, in pasture areas, an additional pressure is introduced by goat herds overgrazing beyond the region´s carrying capacity, which is further limited by the harsher climate condition.

Finally, Fig. 9 shows the total area classified as degraded (moderate, high and very high) and its annual variation for the period of 2000–2016. With the exception of 2011, there is an increase in areas classified as degraded that have accelerated since 2014. During the period of 2000–2011, the region has not been affected by severe droughts (Brito et al., 2017), and the variation observed until 2011 in Fig. 9 is probably associated with abundant rainfall. It is clear that after 2006–2015, there is a significant expansion of areas classified as degraded. The area estimated under different degrees of degradation is approximately 72 000 km^2, according to the estimation of the period of 2007–2016, which represents approximately 4% of the study area.

The area estimated as degraded was 72 708 km^2 in the last period

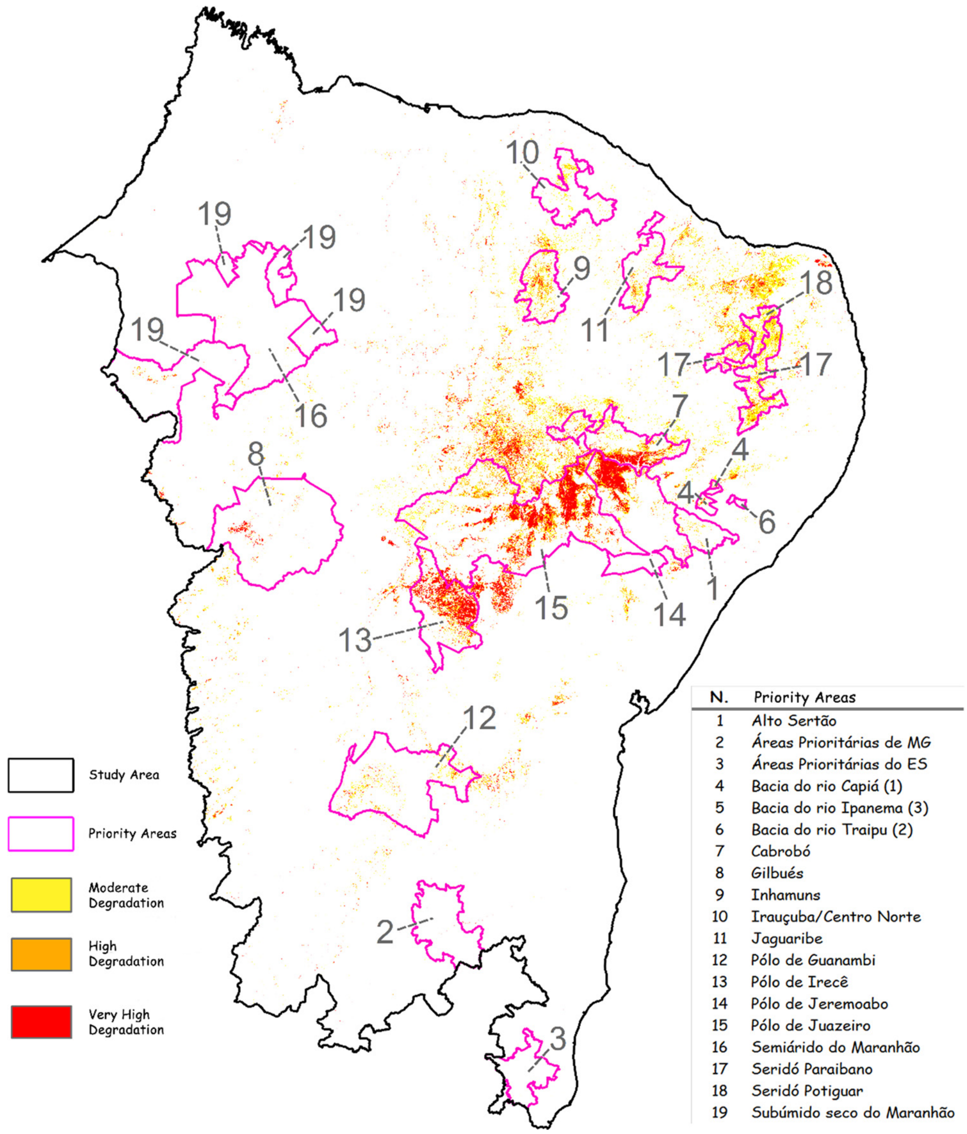


Fig. 7. Degradation map using data of the period.2007–2016.

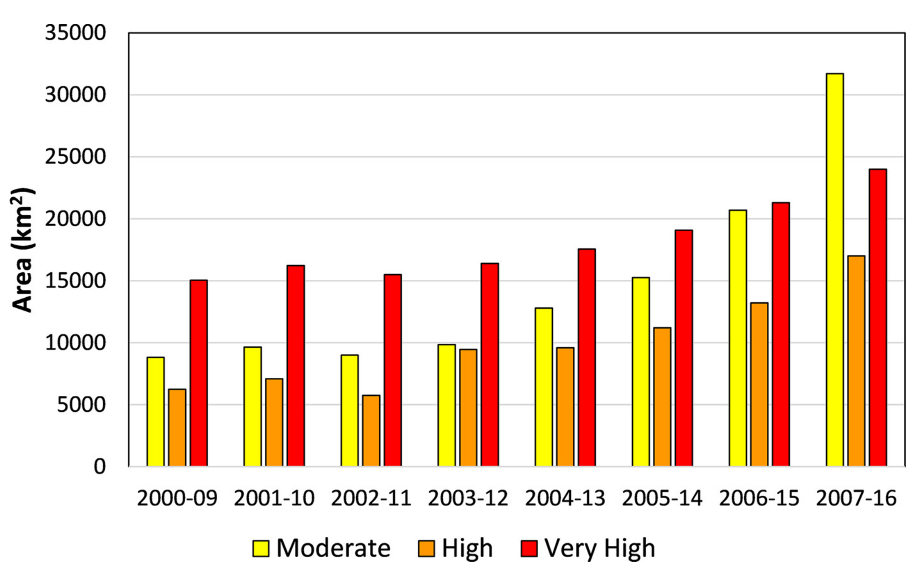
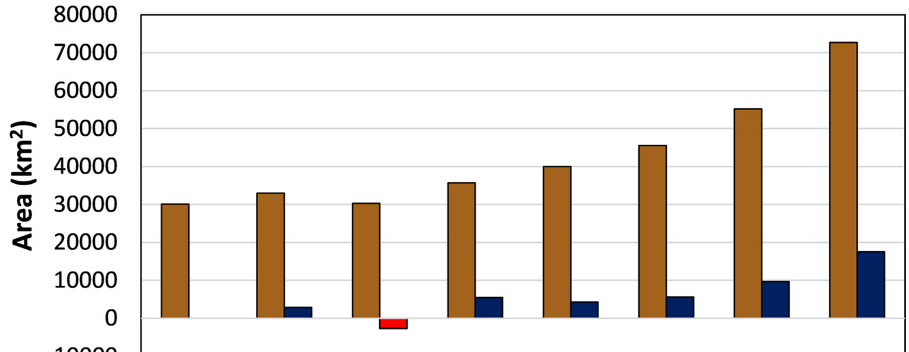


Fig. 8. Time-variation of the area classified as degraded over the period.2000–2016.



	2000-09	2001-10	2002-11	2003-12	2004-13	2005-14	2006-15	2007-16
Total	30111	32950	30262	35694	39966	45535	55189	72708
Variation		2839	-2688	5432	4272	5569	9654	17518

Fig. 9. Total area classified as degraded and annual variation in the period.2010–2016.

(Fig. 9), closer to the values estimated by the Atlas of Desertification of Center for Strategic Studies and Management in Science, Technology and Innovation, which found 70 279 km^2 (CGEE, 2016). Unlike other studies (Sá et al., 2006; CGEE, 2016, among others) the methodology presented here can be easily updated on a yearly basis.

4. Conclusions

The analysis of the trends, based on the NDVI values, was consistent in identifying degraded areas since the better temporal resolution of MODIS information reduces the uncertainties due to cloudiness and allowed for regular monitoring of changes in land use and land cover.

The multi-temporal monitoring of the NDVI classes will allow the identification of areas devoid of vegetation that are more susceptible to desertification, providing guidance for sustainable management of the region.

Soil degradation in the study area is highly related to inadequate and intense land management that exploits natural resources beyond the ecosystem resilience capacity. Combining with evidences from other studies, we concluded that degradation has been enhanced by the severe drought that has affected the region since 2011 by increasing deforestation for the production of firewood and charcoal and the fraction of bare soil.

This study provides the first comprehensive assessment of degradation of the area with such a temporal and spatial resolution. Although we recognized the limitations in the methodology developed, the results are consistent with previous studies with different spatial resolutions. Due to the complexity of the study area with regard to soil and vegetation types that affect the NDVI thresholds defined in this study, more detailed field studies are needed to validate and calibrate the NDVI values at finer scales.

Data availability

Final maps resulting from this study are available on request to the authors.

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