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Monitoring Desertification Using a Small Set of Biophysical Indicators in the Brazilian Semiarid Region

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Abstract: Desertification is defined as land degradation in arid, semiarid, and dry sub-humid regions, and it is caused primarily by human activities and climate change. The semiarid region of Northeast (NE) Brazil is a very large, populous region, and thus, it is hard to monitor the dynamics of its desertified areas; therefore, the present study aimed to develop a minimum set of biophysical indicators to qualify and monitor desertification in this region. This approach included sampling a pair of preserved forested areas and nearby degraded, non-forested areas which had no vegetation growth in the previous years. The study was developed in four stages: (a) pilot site selection; (b) quantification and analysis of soil and vegetation biophysical indicators; (c) biophysical indicator selection; and (d) elaboration of the minimum set of biophysical indicators and desertification levels. Of the analyzed 24 biophysical indicators, 11 were retained and subjected to factor analysis by its principal components. This yielded the minimum set of indicators used to estimate the desertification levels of the pilot sites, which consisted of four soil characteristics: Total Organic Carbon (TOC), cation exchange capacity, clay content, and magnesium content. Regressions were conducted using the SQI, and these indicators showed that the TOC had the highest coefficient of determination. In an exploratory analysis, high SQI (low desertification) showed a positive correlation with the normalized difference vegetation index (R = 0.70) and Aridity Index (R = 0.97). This methodological approach could form the basis of a dynamic monitoring system that is capable of supplying objective, quantitative, and easy to obtain information to decision-makers in NE Brazil and other dry ecosystems around the globe.

Keywords: land degradation; environmental monitoring; soil organic carbon; multiple soil classes; adaptation

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Citation: Perez-Marin, A.M.; Vendruscolo, J.; Zárate-Salazar, J.R.; De Araújo Queiroz, H.A.; Magalhães, D.L.; Menezes, R.S.C.; Fernandes, I.M. Monitoring Desertification Using a Small Set of Biophysical Indicators in the Brazilian Semiarid Region. *Sustainability* **2022**, *14*, 9735. https://doi.org/10.3390/su14159735

Academic Editor: Luca Salvati

Received: 28 May 2022
Accepted: 2 August 2022
Published: 8 August 2022

1. Introduction

The United Nations Convention to Combat Desertification (UNCCD) limits desertification to the dryland regions situated between the longitudinal parallel 30° N and 30° S [1], an area with various degrees of drought that represents approximately 47.2% of the continental area of the planet [2,3]. An estimated 42% of the world's population dwells in this area, and 22% of the world's food production occurs in these environments [4]; this shows the potential impact of desertification processes and climate change [5].

In Brazil, this desertification phenomenon is restricted to the Brazilian Semiarid Region (an area > 1 million km^2 and 13% of the territory of Brazil). Knowledge of degradative processes and their severity are still lacking, and constant updates are needed [6–10]. The population that resides in the Brazilian semi-arid region—approximately 28 million inhabitants and a population density of up to 20 people km^2—is highly dependent on native vegetation to survive; therefore, the potential loss of such vegetation could cause great social, economic, and environmental vulnerability [11,12]. This dependence leads to an increasing pressure on the region's natural resources, consequently making it highly susceptible to desertification processes. Indeed, over the years, it has caused a reduction in arable area, low crop yields, and the silting of rivers and reservoirs, with severe damage caused to productivity, environmental integrity, and farmer profitability [7,13,14].

There are important aspects regarding land tenure, land use, and cover changes that put severe pressure on specific areas. These aspects create a mosaic on the landscape, as preserved and degraded areas are combined due to the fact that they both continue to be impacted by climatic variability and other changes [6,8,9,15]. In Brazil, semiarid, and indeed, anthropic disturbances, are at the core of this degradation process [11,12]. Such processes almost begin with the removal of native vegetation cover, and they favor erosion processes [7,8,15]. Once soil degradation reaches a certain level, its interaction with climate variability may contribute to a turning point that causes the ecosystem to reach the point of no return; this is when vegetation is no longer able to recover, even during the rainy season [8,16–19]. In these areas, the loss of productivity resulting from the degraded land may lead to an increase of anthropic pressure in the surrounding areas to provide subsistence to those local communities [8]. This negative feedback may lead to the degradation of an ever-increasing area. Although signs of degradation in these areas are evident, their organization in a system of quantitative indicators, which tracks the progress of the degradation process, is still incipient, and does not provide results that are consistent with empirical observations. This problem has led to our interest in investigating Brazilian semiarid land.

Conceptually, the UNCCD [1] defines desertification as a process concerning the degradation of land in arid, semiarid, and dry sub-humid areas, the causes of which can be multiple, and the consequences, which are also numerous, are interlinked in a retroactive way [10]. Given this interpretation, desertification has been understood by different scientific disciplines as a complex phenomenon, capable of encompassing structural factors such as social inequality, the concentration of land ownership, access to water, the means of production, biodiversity, and population density [10,20–22]. Furthermore, around the world, several studies have been developed using remote sensing to monitor and evaluate desertification processes [14,23–28]; however, as desertification processes involve many climatic and anthropic factors, only the spectral dynamics are provided by sensors, and thus, the results obtained have not been entirely sufficient to explain this complex phenomenon. Guo et al. [23,24], suggests that to reveal the spatio-temporal changes of the desertification process, which result from the interactive relationships between three or more factors in space–time, 3D or n-D techniques are necessary to fully comprehend the phenomenon of desertification.

Therefore, the entanglement of these factors in the conceptual scope of the UNCCD [1] has contributed to the unclear characterization of a desertified area [10,21,22,28–31]. This hinders the understanding and measurement of the problem, as well as the appropriate awareness of the different social actors involved in the formulation of public policies and decision-making.

Generally speaking, the majority of studies on desertification have focused on social indicators (Human Development Index—HDI, Poverty Index—GINI, education, housing), economic indicators (income per capita, gross domestic product per capita—GDP, poverty), and environmental situations (rainfall, aridity index, Normalized Difference Vegetation Index—NDVI), in order to characterize a merely physical phenomenon (i.e., land degradation). All these indicators are analyzed as parallel, linear, and causal movements, assuming that the mere incorporation of these indicators into the analysis would enable a better qualification of a bio-physical–chemical degradation process of the soil [10,20,22,28–33].

Indicators of social, economic, and environmental impact, although interrelated, are objects of distinct kinds, and the extent to which they frequently arise from indirect or outdated data sources accentuate the possibilities of analytical bias.

Those indicators associated with soil or land degradation have received little attention. The few existing studies that are strictly focused on soil indicators, have been carried out in small areas, thus hindering their extrapolation to surfaces of greater regional dimensions [32–36].

The combination of these aspects, as well as other difficulties, have resulted in the absence of systematic, methodologically robust, and conclusive regional assessments regarding the progression of desertification, which is particularly severe in the case of the Brazilian semiarid region. In this regard, there are still a lack of models, or systems of indicators, that characterize and identify areas that are undergoing the process of desertification or are effectively desertified [21,23,24,27,31–33,37–39].

Studies that assess soil quality indices (SQI) [38–41] can allow an understanding of, and can correlate, desertification levels; this is because the decline in soil quality has an inversely proportional relationship with the advance in soil degradation. Indeed, the reduction of the soil's main ecosystem services contribute to the advancement of desertification [42–45]. Soil quality has been defined as the capacity of a specific kind of soil to function, within natural or managed ecosystem boundaries; to sustain plant and animal productivity; to maintain or enhance water and air quality; and to support human health and habitation [46,47]. Indicators of soil quality are those measurable soil properties and processes that have greatest sensitivity to changes in soil function and its ecosystem services [46,47]. These processes can be developed through the selection of indicators from the total data set and minimum data set; then, these indicators can be scored, interpreted, and subsequently integrated into the processes [39,41–43,45,46]. The latter can be achieved using three types of approaches: Additive, Weighted Additive, and Nemoro. An additional approach that can also be used is the Factorial Weighted Additive [45,46].

Therefore, the present study aims to identify the most appropriate methodological approach in order to propose a minimum set of biophysical indicators for soil and wood; this will enable the assessment and monitoring of the intensity of the process of desertification in the Brazilian semiarid region.

2. Materials and Methods

2.1. Contextualization and Characteristics of the Studied Area

The research was carried out in the semiarid region of Brazil, one of the largest areas that is susceptible to desertification and climate change in the world. The region is approximately 1,127,953 km^2 divided into 1262 municipalities, all of them climatically characterized by a weak relationship between rainfall and evapotranspiration, which results in a water shortage for plants, animals, and humans [5]. About 28 million inhabitants live in this region, of which 10.6 million reside in rural areas and 17.3 million in urban areas [47]. Nevertheless, a significant portion of people who live in urban areas experience a rural lifestyle, since 90% of the municipalities in the semiarid region are classified as being small (less than 50,000 inhabitants). Moreover, the region boasts 1.8 million rural properties, and even though 1.0 million of those properties comprise less than 5.0 hectares of land, they are responsible for 31% of the region's agricultural production [5,47]. Most of the Brazilian semiarid region suffers from low economic growth, a lack of basic infrastructure, and social indicators below the national and regional average. The GDP per capita (BRL 6520.00) is 67% lower than the Brazilian average, and the illiteracy rate fluctuates between 36% and 46% in approximately 46% of the municipalities. About 60% of these have low HDI (0.5 to 0.59) [47].

It is evident, therefore, that the semiarid region of NE Brazil is a very complex region that is characterized by extreme environmental and socioeconomic variability [10,17]. The tropical dry forest vegetation that is native to NE Brazil, also known as "Caatinga vegetation," still covers approximately half of the semiarid region [48,49]. Most of the area that is currently covered by forests is occupied by secondary forest vegetation that is being regenerated after deforestation for fuelwood extraction, or the cultivation of crops and pastures [49,50]. As a result, this dynamic land-use shift created landscapes that are characterized by a mosaic of pastures, agricultural fields, and forest patches at different levels of succession, ranging from disturbed/open forests to dense forest fragments [17,50,51]. The environmental variability is also intensified due to the large diversity of soil types across the region, which respond differently to the natural and anthropic pressures that may lead to soil degradation and desertification [17].

2.2. Methodological Procedures

The research was carried out in four steps (Figure 1), as follows:

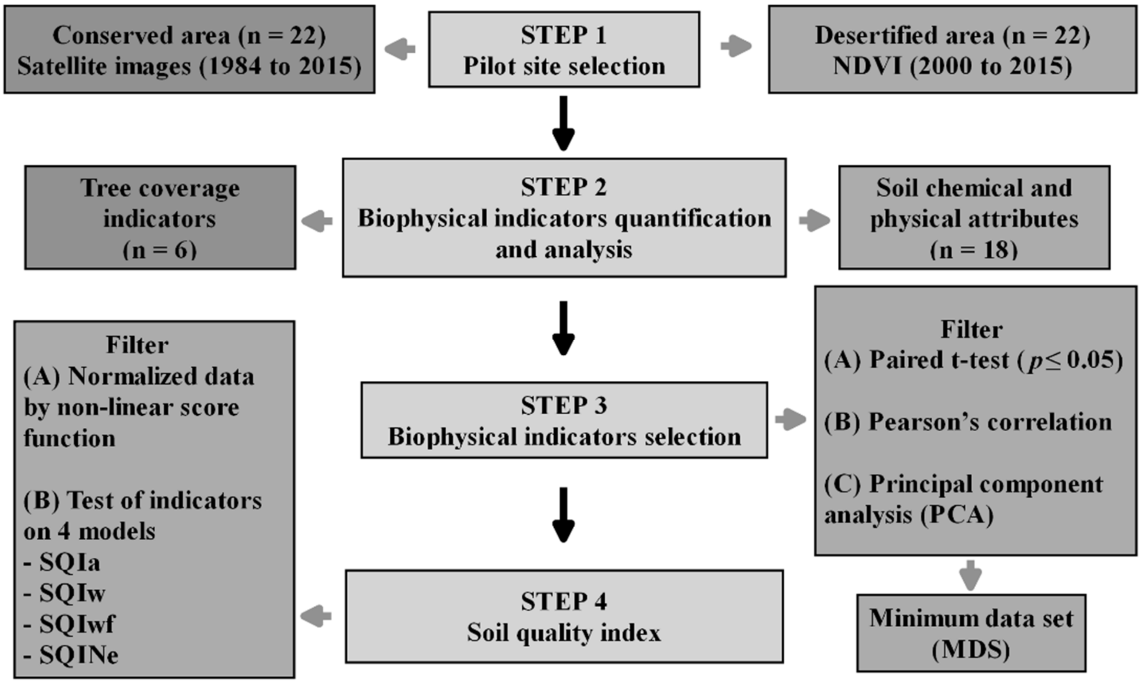


Figure 1. Steps for measuring and determining the desertification level in the Brazilian semiarid region.

2.2.1. Step 1—Pilot Site Selection

In order to develop and propose a minimum set of biophysical indicators, we chose areas that were specific to, and representative of, the region. We also ensured that they were able to be studied as pilot sites in order to enable a better approximation of the phenomenon, which thus made it possible to approach it at a local level, while equally ensuring that we could also extrapolate it to the regional level. We selected 44 pilot sites (Figure 2), with 22 of them considered as well-preserved, and the remaining 22 showing clear signs of desertification; for instance, they presented no vegetation growth in previous years, even during the rainy season.

The desertification process reduces the richness of woody species and causes modifications to the woody structure of the Caatinga biome, thus reducing soil protection against pluviometric precipitation as well as incidences of sunlight [50]. In this context, desertified sites (DS) were selected based on the difficulty of restoring its dry forest vegetation cover (Figure 3) in previous years, and on how often they were subject to erosion processes. During this selection process, we analyzed the Normalized Difference Vegetation Index (NDVI) over a period of $\geq$5 years (1999/2000 to 2015) (Appendix A), which was obtained from the images of the Landsat 5 and Landsat 8 satellites, with the aid of the Google Earth Engine tool. The period during which the images were taken matched the period of higher rainfall and low incidence of clouds, and thus excluded water as a limiting factor for plant growth; therefore, the DS corresponded with areas of severely degraded soil that hindered vegetation growth and development [50].

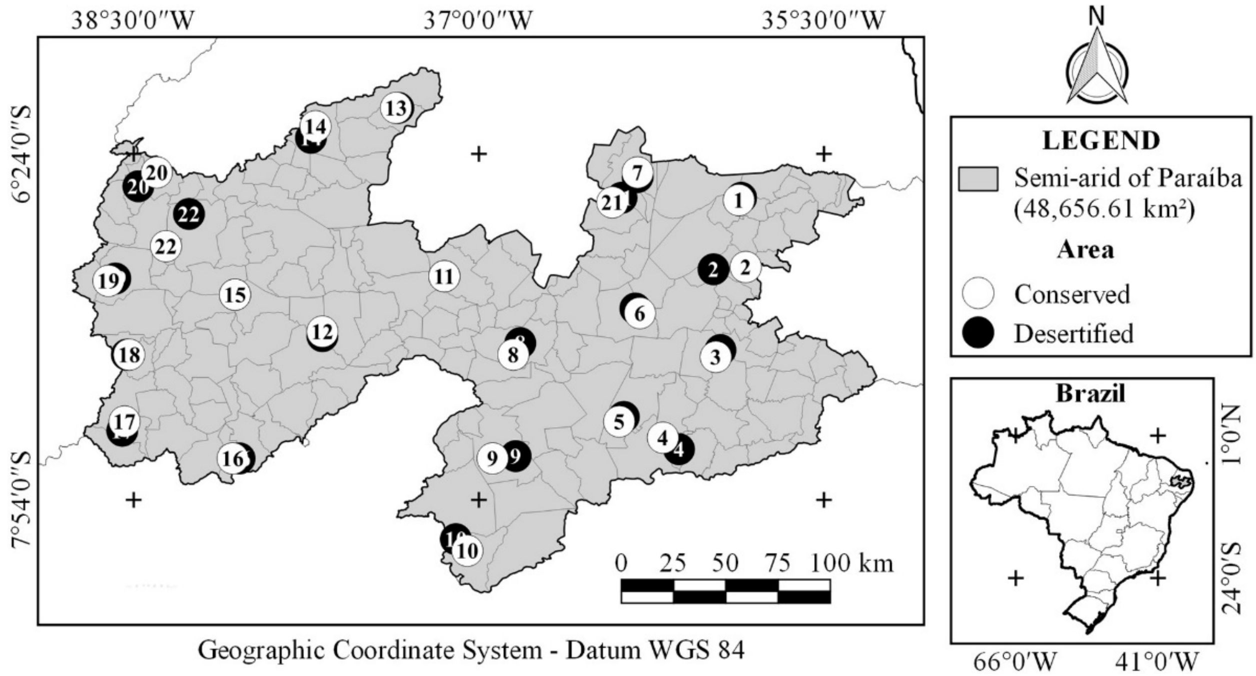


Figure 2. Distribution and location of the 44 selected pilot sites (22 conserved and 22 desertified) in the semiarid region of the state of Paraíba, NE Brazil.

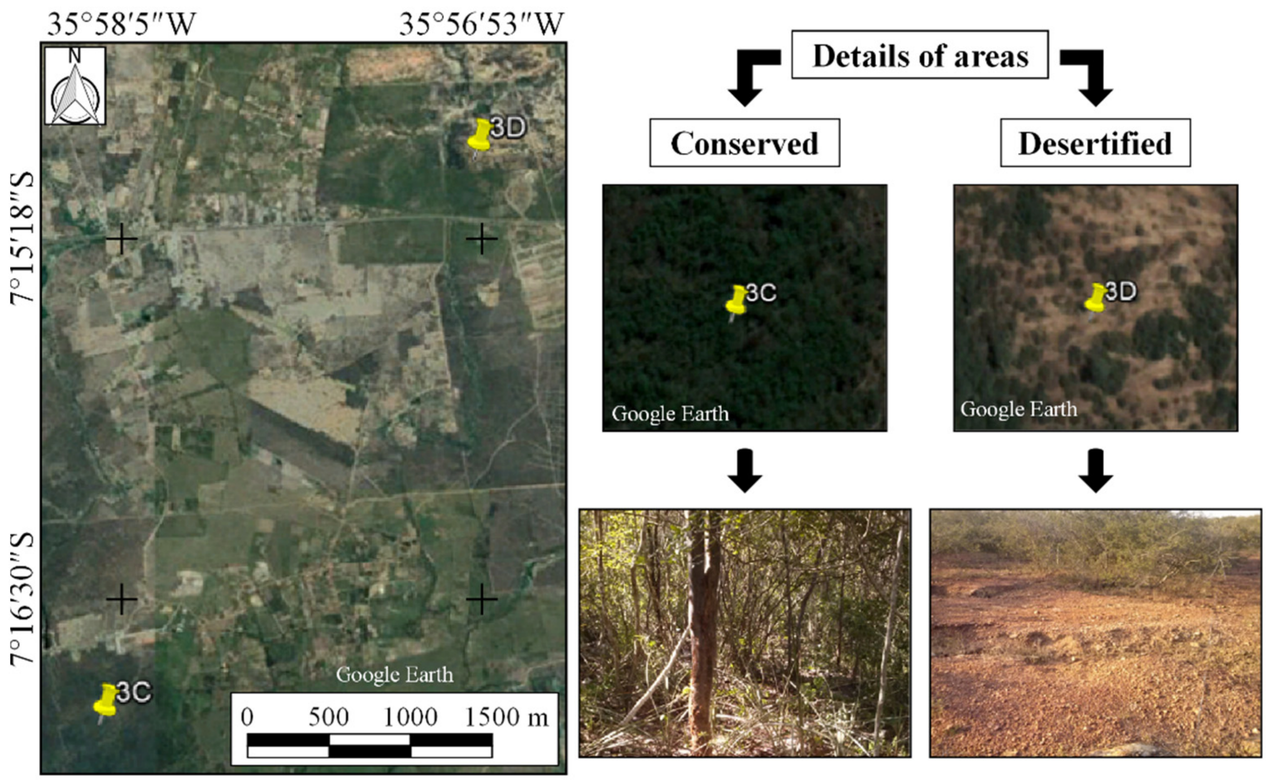


Figure 3. Details of the selected desertified and conserved pilot sites in the semiarid region of NE Brazil. 3C = Conserved areas and 3D = desertified areas.

The conserved areas (CA) were selected after considering the absence of clear-cutting, which had not taken place since 1984, according to temporal images from the past 28 years, using the Landsat Annual Timelapse 1984–2012 (Figure 3). Subsequently, the selected areas were compared with updated images from Landsat 8 and confirmed in the field. After the selection of the areas, each pilot site was located using the Google Earth program and GPS navigation (60CSx Garmin, Garmin International, Inc., Olathe, KS, USA).

2.2.2. Step 2—Biophysical Indicators' Quantification and Analysis

In each pilot site, we implemented a 100 m^2 (10 m $\times$ 10 m) plot and evaluated the following parameters: number of woody species (NSp), woody plant density (PD), average canopy height (H-A), average circumference at the base (CB-A), average circumference at breast height (CBH-A); total absolute dominance (AD-T); basal area (BA); and volume of biomass (VOL). Then, we collected a composite soil sample (from five sub-samples) from the 0–20 cm layer for chemical and physical analysis, in accordance with the methods described by Embrapa [52]. The soil samples were previously packed into identified plastic bags, taken to the laboratory, air dried, sifted through a 2 mm sieve, and the active acidity (pH in water), potential acidity (H+Al), sodium content (Na^+), aluminum content (Al^{3+}), potassium content (K^+), calcium content (Ca^{2+}), magnesium content (Mg^{2+}), total organic carbon (TOC) content, available P (Mehlich-1), sum of bases (SB), effective cation exchange capacity (CEC), potential CEC, base saturation (BS), exchangeable sodium percentage (ESP), particle size, and total porosity (TP) were analyzed. Undisturbed samples (132) were also collected to analyze the bulk density [52]. The total data set (24 variables of both areas) was subjected to the Kolmogorov–Smirnov and Bartlett test to check for normality and homoscedasticity ($p > 0.05$), respectively.

2.2.3. Step 3—Biophysical Indicator Selection

The selection was performed in three steps. First, we used the paired t-test to identify statistical differences between the desertified and conserved sites ($p \leq 0.05$) for the biophysical indicators of soil and vegetation cover. In the second step, we used Pearson's correlation to analyze the collinearity of indicators in soil and vegetation cover, which showed significant differences between groups (desertified and conserved). During the third step, indicators with significant correlation values $\leq$0.80 were used. During the final step, we retained and submitted the non-redundant indicators to account for analysis that was related to principal components analyses (PCA) [46,53]; this was carried out to reduce the number of independent indicators [11] and to form the minimum data set (MDS).

We selected the principal components (PC) with eigenvalues >1 [54] that explained more than 5% of the data variance [55]. When more than one variable was retained in a PCA, the coefficients of the multivariate correlation were analyzed to determine whether they could be retained when their coefficients were lower than 0.60 [42]; however, if the indicators were significantly correlated (r > 0.60) in a PCA, the variable with the largest sum of correlation was selected for the MDS [53].

2.2.4. Step 4—Selection of the Desertification Indicators

First, the indicators that were used for the MDS were normalized by the non-linear score function [56], as suggested by Nabiollahi et al. [46]; thus, we used the sigmoidal equation (Equation (1)):

$$NLS = \frac{a}{1 + \left(\frac{X}{X0}\right)^{b}} \tag{1}$$

where: NLS = non-linear score of the variable, between 0 and 1; a = maximum score, equal to 1; X = value of the variable; X_0 = average value of the variable; b = slope assumed as -2.5 for functions of 'more is better', and +2.5 for 'minus is better' [57].

Subsequently, the standardized indicators for the MDS were integrated and tested using the four approaches in the determination of soil quality index (SQI):

First Model: Additive Soil Quality Index (SQI_a), adapted from Andrews et al. [42], (Equation (2)).

$$SQI_a = \frac{\sum_1^n N_i}{n} \quad (2)$$

Second Model: Weighted Additive Soil Quality Index (SQI_w), adapted from Doran and Parkin [58], and Liu et al. [59], (Equation (3)).

$$SQI_w = \sum_1^n W_i * N_i \quad (3)$$

Third Model: Weighted Factorial Additive Soil Quality Index (SQI_{wf}), adapted from Biswas et al. [45], (Equation (4)).

$$SQI_{wf} = \sum_1^n W_i * N_i \quad (4)$$

Fourth Model: Nemoro Soil Quality Index (SQI_{Ne}), adapted from Qin [51], (Equation (5)).

$$SQI_{Ne} = \sqrt{\frac{Saver2 + Smin2}{2}} * \left(\frac{n-1}{n}\right) \quad (5)$$

where: N_i = scores or record of the indicators; W_i = weight of each indicator; *Saver* = average of scores; *Smin* = minimum value of the scores for each indicator in the MDS; and n = number of indicators.

Two types of weights (W_i) were calculated. For Equation (2) (Weighted Additive), the weight was calculated from communality [58,59], and for Equation (3) (Weighted Factorial Additive), the weight was calculated from the factor analysis of principal components [45].

In terms of interpretation, in the present study, the Soil Quality Index (SQI) should be understood as being inversely proportional to the Desertification Index (ID) (i.e., the higher the SQI, the less degraded the area, and vice versa, according to Table 1) [46].

Table 1. Scale and classes of soil quality index (SQI) levels, and their correspondence with conservation levels and degradation.

Class	[1] SQI Scale	Conservation Level	DI Scale [2]	Degradation Level
I	>0.78	Very high	<0.22	Very Low
II	0.62–0.78	High	0.22–0.38	Low
III	0.47–0.62	Moderate	0.38–0.53	Moderate
IV	0.31–0.47	Low	0.53–0.69	High
V	<0.31	Very low	>0.69	Very High

[1] Adapted from Nabiollahi et al. [46]; [2] calculated, ID = 1 − SQI, where 1 is the maximum level for desertification.

Next, we evaluated the performance of each method so that it could be given a place in the SQI; this was achieved via linear regression analyses between the indicators of the MDS and their respective SQI. Based on these analyses, we selected the SQI that had the highest correlation with the indicators of the MDS.

3. Results

3.1. Paired t-Test between Pilot Sites and Biophysical Indicators

Of the 24 biophysical indicators (soil and woody coverage) of the pilot sites, 17 showed significant differences (p = 0.05): eight chemical indicators (P, Na, Ca, Mg, H+Al, CEC, TOC, and ESP), three physical indicators (clay, BD, and TP), and six indicators of arboreal coverage (Nsp, PD, AD-T, H-A, BA, and VOL) (Table 2). There was no significant difference between the desertified and conserved areas in terms of pH, K, sum of bases, effective CEC, saturation of bases (SB), or silt and sand fractions.

Table 2. Biophysical indicators of the soil and woody coverage of the pilot areas in semiarid NE Brazil.

Soil Chemical Indicators	Unit	Conditions of Pilot Sites	
		Conserved (*n* = 22)	Degraded (*n* = 22)
Soil pH in water	logarithmic	6.29 ± 0.14 a	6.21 ± 0.15 a
Available P	mg kg^{-1}	13.05 ± 0.24 a	10.62 ± 0.25 b
Exchangeable K^+	mg kg^{-1}	140.07 ± 0.21 a	151.82 ± 14.79 a
Exchangeable Na^+	$cmol_c$ kg^{-1}	0.06 ± 0.00 b	0.16 ± 0.00 a
Exchangeable Ca^{2+}	$cmol_c$ kg^{-1}	7.09 ± 0.60 a	4.56 ± 0.31 b
Exchangeable Mg^{2+}	$cmol_c$ kg^{-1}	2.26 ± 0.20 b	2.90 ± 0.21 a
Potential acidity (H+Al)	$cmol_c$ kg^{-1}	3.02 ± 0.34 a	1.84 ± 0.3 b
Sum of bases (SB)	$cmol_c$ kg^{-1}	9.65 ± 0.85 a	7.94 ± 0.18 a
Effective Cation Exchange Capacity (CEC)	$cmol_c$ kg^{-1}	9.67 ± 0.85 a	8.28 ± 0.22 a
Cationic Exchange Capacity (potential CEC)	$cmol_c$ kg^{-1}	12.67 ± 0.87 a	10.06 ± 1.14 b
Total Organic Carbon (TOC)	g kg^{-1}	28.06 ± 1.83 a	3.13 ± 0.37 b
Base saturation (BS)	%	75.32 ± 2.85 a	78.55 ± 3.28 a
Exchangeable Sodium Percentage ESP)	%	0.59 ± 0.02 b	1.81 ± 0.28 a
Soil physical indicators			
Total Sand	g kg^{-1}	620.29 ± 28.70 a	642.36 ± 26.41 a
Silt	g kg^{-1}	221.46 ± 18.95 a	232.85 ± 17.80 a
Clay	g kg^{-1}	158.22 ± 13.41 a	124.75 ± 0.20 b
Bulk density (BD)	kg m^{-3}	1.14 ± 0.03 b	1.45 ± 0.03 a
Total porosity (TP)	%	0.57 ± 0.01 a	0.45 ± 0.01 b
Arboreal coverage indicators			
No. species (Nsp)	Number	9.82 ± 0.62 a	1.94 ± 0.18 b
Plant density (PD)	Ind. ha^{-1}	4818.18 ± 305.62 a	872.51 ± 0.15 b
Total Absolute dominance (AD-T)	m^2 ha^{-1}	18.18 ± 0.27 a	1.02 ± 0.1 b
Average canopy height (H-A)	M	4.09 ± 0.15 a	2.07 ± 0.16 b
Basal area (BA)	m^2 ha^{-1}	0.10 ± 0.01 a	0.03 ± 0.00 b
Volume of biomass (VOL)	(m^3 ha^{-1})	2.00 ± 0.22 a	0.49 ± 0.02 b

Different letters indicate statistical differences between soil indicators in the conserved and degraded areas within the pilot sites, in accordance with the Student's *t*-test at a 5% significance level ($p < 0.05$).

3.2. Pearson Correlation between the Biophysical Indicators of the Pilot Sites

The TOC was the variable with the highest percentage (+70%) of positive and significant correlations between the 17 indicators, whereas Na^+ and BD were the indicators with the highest number of negative correlations (Table 3). Among them, the well-correlated indicators ($r > 0.6$) were considered to be redundant, and only one of them was retained for the PCA [46,60]; therefore, 11 of the 17 indicators were retained, seven were related to chemical indicators (P, Ca^{2+}, Mg^{2+}, H+Al, CEC, TOC, ESP), two were related to physical indicators (Clay, BD), and two were related to the woody coverage (BA and VOL). These indicators were submitted for factor analysis and principal components analysis (PCA), and thus, they constitute a MDS.

Table 3. Pearson correlation coefficients of the biophysical indicators of soil and woody coverage in the pilot sites.

	P	**Na^+**	**Ca^{2+}**	**Mg^{2+}**	**H+Al**	**CEC**	**TOC**	**ESP**	**Clay**	**BD**	**PT**	**Nsp**	**PD**	**H-A**	**AD-T**	**BA**
Na^+	−0.73 ***	1														
Ca^{2+}	0.41 **	−0.50 ***	1													
MgV	−0.21	0.32 *	−0.29	1												
H+Al	0.29	−0.38 *	0.14	−0.05	1											
CEC	0.06	−0.27	0.45 **	0.08	0.27	1										
TOC	0.72 ***	−0.90 ***	0.63 ***	−0.35 *	0.43 **	0.37 *	1									
ESP	−0.30	0.56 ***	−0.26	0.06	−0.20	−0.41 **	−0.46 **	1								
Clay	0.19	−0.36 *	0.62 ***	−0.19	0.12	0.40 **	0.53 ***	−0.19	1							
BD	−0.66 ***	0.78 ***	−0.34 *	0.41 **	−0.29	−0.17	−0.75 ***	0.42 **	−0.13	1						
PT	0.66 ***	−0.78 ***	0.34 *	−0.41 **	0.29	0.17	0.75 ***	−0.42 **	0.13	−1 ***	1					
Nsp	0.62 ***	−0.88 ***	0.45 **	−0.34 *	0.28	0.30	0.76 ***	−0.53 ***	0.27	−0.74 ***	0.74 ***	1				
PD	0.62 ***	−0.89 ***	0.38 *	−0.36 *	0.20	0.14	0.74 ***	−0.51 ***	0.38 *	−0.70 ***	0.70 ***	0.84 ***	1			
H-A	0.69 ***	−0.82 ***	0.40 **	−0.05	0.30 *	0.32 *	0.75 ***	−0.48 **	0.23	−0.64 ***	0.64 ***	0.78 ***	0.61 ***	1		
AD-T	0.73 ***	−0.99 ***	0.49 ***	−0.31 *	0.38 *	0.26	0.89 ***	−0.56 ***	0.33 *	−0.77 ***	0.77 ***	0.87 ***	0.89 ***	0.80 ***	1	
BA	0.60 ***	−0.67 ***	0.31 *	−0.12	0.22	0.18	0.61 ***	−0.36 *	0.19	−0.59 ***	0.59 ***	0.55 ***	0.61 ***	0.53 ***	0.68 ***	1
VOL	0.70 ***	−0.72 ***	0.32 *	−0.21	0.41 **	0.19	0.64 ***	−0.40 **	0.17	−0.66 ***	0.66 ***	0.57 ***	0.66 ***	0.61 ***	0.72 ***	0.65 ***

P: Phosphorus available content; Na: Exchangeable Sodium content; Ca: Exchangeable Calcium content; Mg: Exchangeable Magnesium content; H+Al: Potential acidity; CEC: Cation Exchange Capacity; TOC: Total Organic Carbon; ESP: Sodium Percentage; Clay: Clay content; BD: Bulk Density; PT: Porosity; Nsp: No. of Woody Species; PD: Woody Plant Density; H-A: Average canopy height; AD-T Absolute dominance; BA: Basal area; and VOL: Volume of biomass. ***, ** and * indicate 0.001, 0.01, and 0.05 significance level, respectively.

3.3. Principal Component Analysis of the Minimum Set of Biophysical Attributes of the Pilot Sites

The principal components analysis (PCA), which occurred after the Varimax rotation, showed that approximately 68.84% of the variation found in this study was explained by the biophysical indicators of the soil and arboreal coverage; these were retained in the first three principal components (eigenvalues > 1 and variance > 5%; Table 4).

Table 4. Principal components analysis of the significant biophysical indicators of soil and woody coverage in the pilot sites in semiarid NE Brazil.

Biophysical Indicators	PC1	PC2	PC3
Eigenvalues	4.7846	1.5756	1.2125
Percentage variance	<u>43.4965</u>	<u>14.3235</u>	<u>11.0232</u>
Cumulative percentage variance	43.4965	57.8200	<u>68.8432</u>
Eigenvectors			
Available P	0.7810	−0.3440	−0.0622
Exchangeable Ca^{2+}	0.6528	0.5117	−0.2913
Exchangeable Mg^{2+}	−0.3635	0.0958	**0.7273**
Potential acidity (H+Al)	0.4588	−0.0337	0.3909
Total Cation Exchange Capacity	0.4287	**0.6450**	0.4096
Total Organic Carbon	**0.9317**	0.0636	−0.0884
Exchangeable Sodium Percentage	−0.5636	−0.1077	−0.3927
Clay	0.4829	**0.6726**	−0.2617
Bulk density	−0.8031	0.3353	0.0866
Basal Area	0.7255	−0.2765	0.1273
Volume of biomass	0.7949	−0.3351	0.1418

Underlined values were used to obtain the weight factorial additive of SQI_{wf} (Equation (3)), and values in bold stood out as the most significant vectors to consider when choosing an indicator.

In the vector projection and two-dimensional ordination (Figure 4), we can see the distinction between the pilot sites, regarding the level of conservation or degradation, and the indicators that most influenced this distinction, as well as the greater or lesser sensitivities of the 11 indicators analyzed. The diagram also makes it clear that the pilot sites formed four groups, which are distinguishable in a gradient showing either degradation or conservation.

The indicators TOC, P, H+Al, Ca^{2+}, BA, PD, VOL, clay, and CEC are more closely associated with areas of high and moderate conservation, whereas, conversely, the indicators BD, Mg^{2+}, and ESP are related to areas of moderate, high, and very high degradation (low SQI), thus indicating the sensitivity of these indicators to the distinctions between the studied environments.

Therefore, the PC1 explained 43.5% of the total variation of the studied indicators and presented the highest correlation coefficients (>0.70); the TOC was the most heavily weighted indicator on PC1, as it had the highest absolute value (0.93) within the 10% of indicators that had an increased factor load, and it was positively correlated with the majority of the indicators (Table 4). PC2 and PC3 explained 14.3% and 11.02% of the total variation of the indicators studied, respectively. Clay and CEC were retained on PC2, since both had the same sum of correlations (Table 5). On the other hand, only Mg^{2+} was retained on PC3, due to its higher factor loading (Table 4).

Consequently, the biophysical indicators (soil TOC, clay, CEC, and Mg^{2+}) were retained for the MDS and used to estimate the SQI of the sites. To interpret the scores using the 'more is better', 'less is better', and 'great is better' approaches, the descriptive statistics of the MDS were observed (Table 6). We saw that the clay and Mg^{2+} did not reach the optimal values recommended by the literature, and thus, for the MDS, we adopted the 'more is better' approach, using the sigmoid curve.

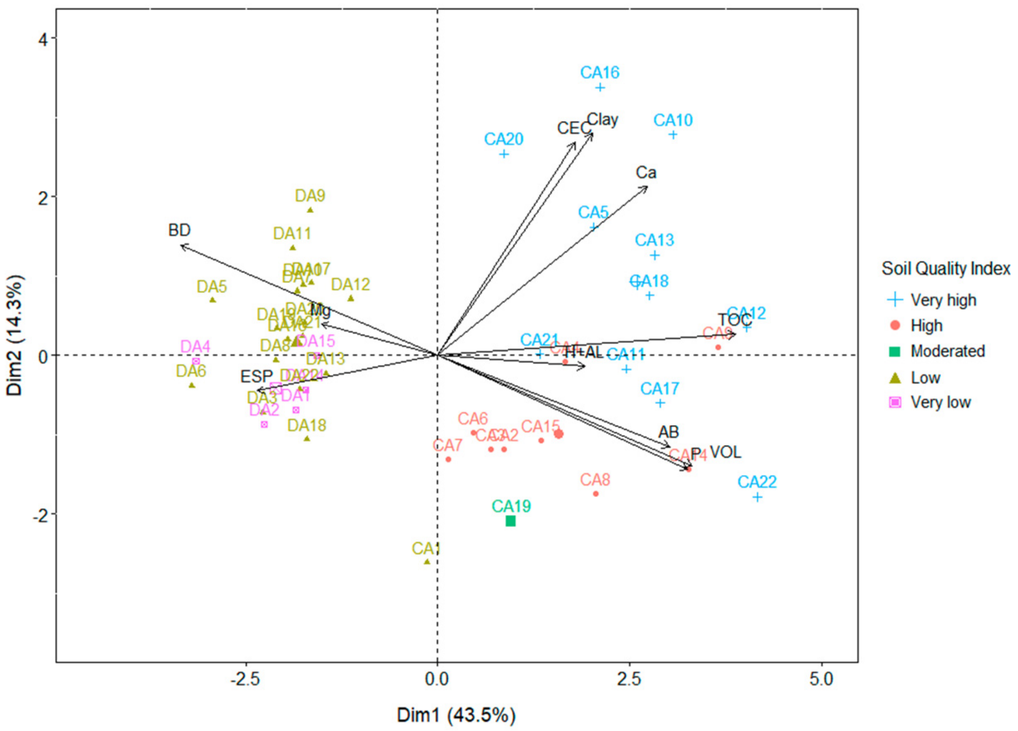


Figure 4. Principal components analysis (PCA) of the biophysical indicators of soil and woody coverage in the pilot sites undergoing different levels of degradation or conservation. P: available phosphorus; TOC: Total organic carbon; CEC: cation exchange capacity; H+Al: hydrogen and exchangeable aluminum; Ca^{2+}: exchangeable calcium; Mg^{2+}: exchangeable magnesium; Na^{+}: exchangeable sodium; ESP: exchangeable sodium percentage; Clay: percentage of clay; PD: Plant density; BA: basal area; and VOL: volume of biomass.

Table 5. Coefficients and sums of correlations of the minimum set of biophysical indicators of the pilot sites, heavily weighted, in principal components (PC), with multiple high factor loadings.

Indicators of PC2	Cation Exchange Capacity (CEC)	Clay
Cation Exchange Capacity (CEC)	1.00	0.40
Clay	0.40	1.00
Sum of correlations	1.40	1.40

Table 6. Minimum, maximum, and average values of the minimum set of biophysical indicators retained on the minimum data set (MDS).

Soil Indicator	Unit	Minimum	Maximum	Average	SD
Total Organic Carbon (TOC)	g kg^{-1}	0.62	39.82	15.60	14.02
Cation Exchange Capacity (CEC)	$cmol_c$ kg^{-1}	2.89	23.16	11.37	4.88
Clay	%	4.00	24.00	14.00	5.00
Mg^{2+}	$cmol_c$ kg^{-1}	0.56	5.15	2.58	1.01

The weights of the minimum set of biophysical indicators that determine the SQI of the pilot sites using the Weighted Additive and Weighted Factorial Additive methods by Doran and Parkin [58], Liu et al. [59], and Biswas et al. [45], are summarized in Table 7.

Table 7. Estimates of communality and the weights of the minimum set of biophysical indicators of the pilot sites.

MSD Indicators	COM [1]	Weight [2]	Factor Weight [3]
Exchangeable Mg^{2+}	0.8693	0.2853	0.6318
Cation Exchange Capacity (CEC)	0.7661	0.2514	0.2081
Total Organic Carbon (TOC)	0.7377	0.2421	0.2081
Clay	0.6744	0.2213	0.1601

[1] COM: communality of each soil property [58]; [2] weights calculated as a function of communality [59]. [3] Factorial weights calculated as a function of the percentage of variation and the percentage of accumulated variation [45].

Based on the results presented in Table 7, we determined the equations for the methods SQI_w and SQI_{wf} (Table 8), which enabled us to understand the respective desertification indices (DI) for all sites.

Table 8. Final equations for the calculation of the soil quality index, based on the minimum set of biophysical indicators of the pilot sites.

Model for the Soil Quality Index (SQI)	Equations for the Calculation for the SQI
Weighted Additive [38,39]	$\boldsymbol{SQI_w}$ = ∑(Score of Total Organic Carbon × 0.2421) + (Score of Cationic Exchange Capacity × 0.2514) + (Score of the percentage of clay × 0.2213) + (Score of Mg^{2+} × 0.2853)
Weighted Factorial Additive [24]	$\boldsymbol{SQI_{wf}}$ = ∑(Score of Total Organic Carbon × 0.6318) + (Score of Cationic Exchange Capacity × 0.2081) + (Score of the percentage of clay × 0.2213) + (Score of Mg^{2+} × 0.1601)

In Figure 5, we can see that the weighted additive method (SQI_{wf}), as proposed by Biswas et al. [45], was the most appropriate and comprehensive of the methods used for the calculation of the desertification or conservation indices of the pilot sites. The performances of the desertification indices, calculated using different methods, emerged in the following order: $SQI_{wf} > SQI_w = SQI_a > SQI_{Ne}$.

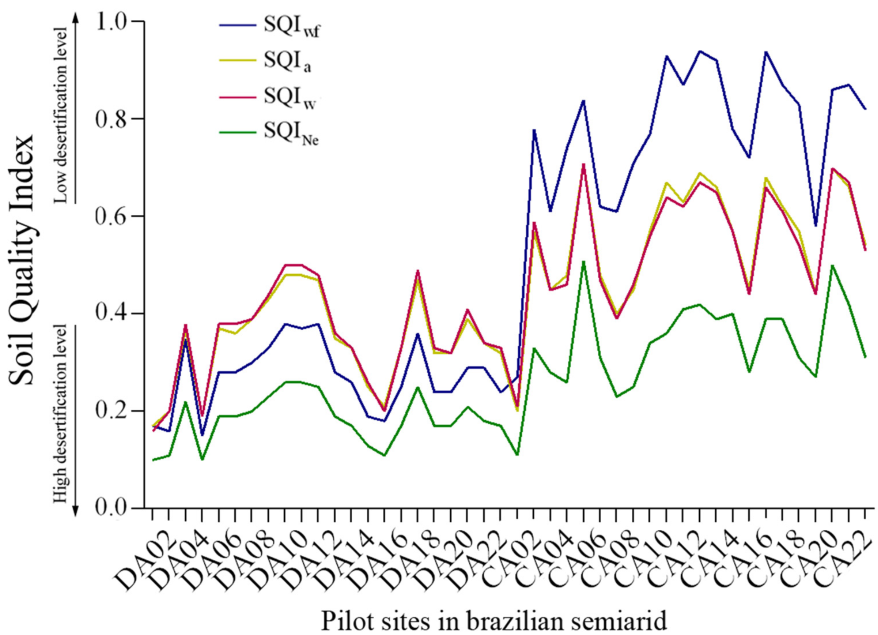


Figure 5. Distribution of the desertification indices (DI) in different pilot sites. DA1 to DA22: desertification area; CA1 to CA22: conservation area; SQI_{wf}: weighted factorial additive soil quality index; SQI_a: additive soil quality index; SQI_w: weighted additive soil quality index; SQI_{Ne}: Nemoro soil quality index.

Using linear regression methods to ascertain the soil quality indices and the minimum set of biophysical indicators (Table 6), we observed that the Total Organic Carbon had the best coefficient of determination out of all SQI methods (SQI_a, SQI_W, SQI_{Wf}, and SQI_{Ne}) (Table 9).

Table 9. Relationship between biophysical indicators of a minimum data set and the method for the calculation of the soil quality index (SQI). R^2 = coefficient of determination.

Calculation Model of the Soil Quality Index	Regression Equation	R^2
Additive [42]	SQI_a = 0.0085 × Total Organic Carbon + 0.3155	0.6120
	SQI_a = 0.0223 × Total cation exchange capacity + 0.1950	0.5071
	SQI_a = 2.1639 × Percentage of clay + 0.1426	0.4428
	SQI_a = 0.0184 Mg exchangeable + 0.4012 *	0.0146
Weighted Additive [58,59]	SQI_W = 0.0080 × Total Organic Carbon + 0.3248	0.5622
	SQI_W = 0.0219 × Total cation exchange capacity + 0.2001	0.5153
	SQI_W = 2.0013 × Percentage of clay + 0.1660	0.3994
	SQI_W = 0.0277 Mg exchangeable + 0.3776 *	0.0349
Weighted Factorial Additive [45]	SQI_{Wf} = 0.0189 × Total Organic Carbon + 0.22236	0.9089
	SQI_{Wf} = 0.0297 × Total cation exchange capacity + 0.1811	0.2718
	SQI_{Wf} = 3.5214 × Percentage of clay + 0.0207	0.3436
	SQI_{Wf} = −0.0490 × Mg exchangeable + 0.6455	0.0313
Nemoro [51]	SQI_{Ne} = 0.0059 × Total Organic Carbon + 0.1695	0.5842
	SQI_{Ne} = 0.0136 × Total cation exchange capacity + 0.1071	0.3772
	SQI_{Ne} = 1.4844 × Percentage of clay + 0.0512	0.4204
	SQI_{Ne} = 0.0138 Mg exchangeable + 0.2256 *	0.0165

* Significant, in accordance with linear regression analysis ($p < 0.05$).

SQ_{wf} had a significant correlation, with a coefficient of determination greater than 95% for the total organic carbon in the soil, whereas for SQI_a, SQI_{Ne} and SQI_w, the correlation coefficients were 0.78, 0.76, and 0.75, respectively (Table 10); therefore, the performance order was $SQI_{wf} > SQI_a > SQI_{Ne} > SQI_w$, meaning that SQI_{wf} was the best method for the determination of the desertification index. Hence, the Total Organic Carbon concentration in the soil was the best indicator for this purpose.

Table 10. Pearson correlation coefficients for the methods used in the soil quality index (SQI), and the Total Organic Carbon (TOC) concentration in the soil, in the pilot study sites. Models for the soil quality index: SQI_a = Additive; SQI_w = Weighted Additive; SQI_{wf} = Weighted Factorial Additive; SQI_{Ne} = Nemoro.

	TOC	SQI_a	SQI_w	SQI_{wf}	SQI_{Ne}
TOC	1				
SQI_a	0.78 ***	1			
SQI_w	0.75 ***	1 ***	1		
SQI_{wf}	0.95 ***	0.92 ***	0.90 ***	1	
SQI_{Ne}	0.76 ***	0.97 ***	0.97 ***	0.91 ***	1

*** Significant, in accordance with the Pearson correlation ($p < 0.001$).

We can see that the TOC was the attribute that had the best coefficient of determination with SQI_{wf} (>0.90) when compared with the other indicators that compose the MDS (Figure 6A). The indicators Mg^{2+}, CEC, and clay had a determination coefficient <0.40, which is considered to beweak (Figure 6B–D).

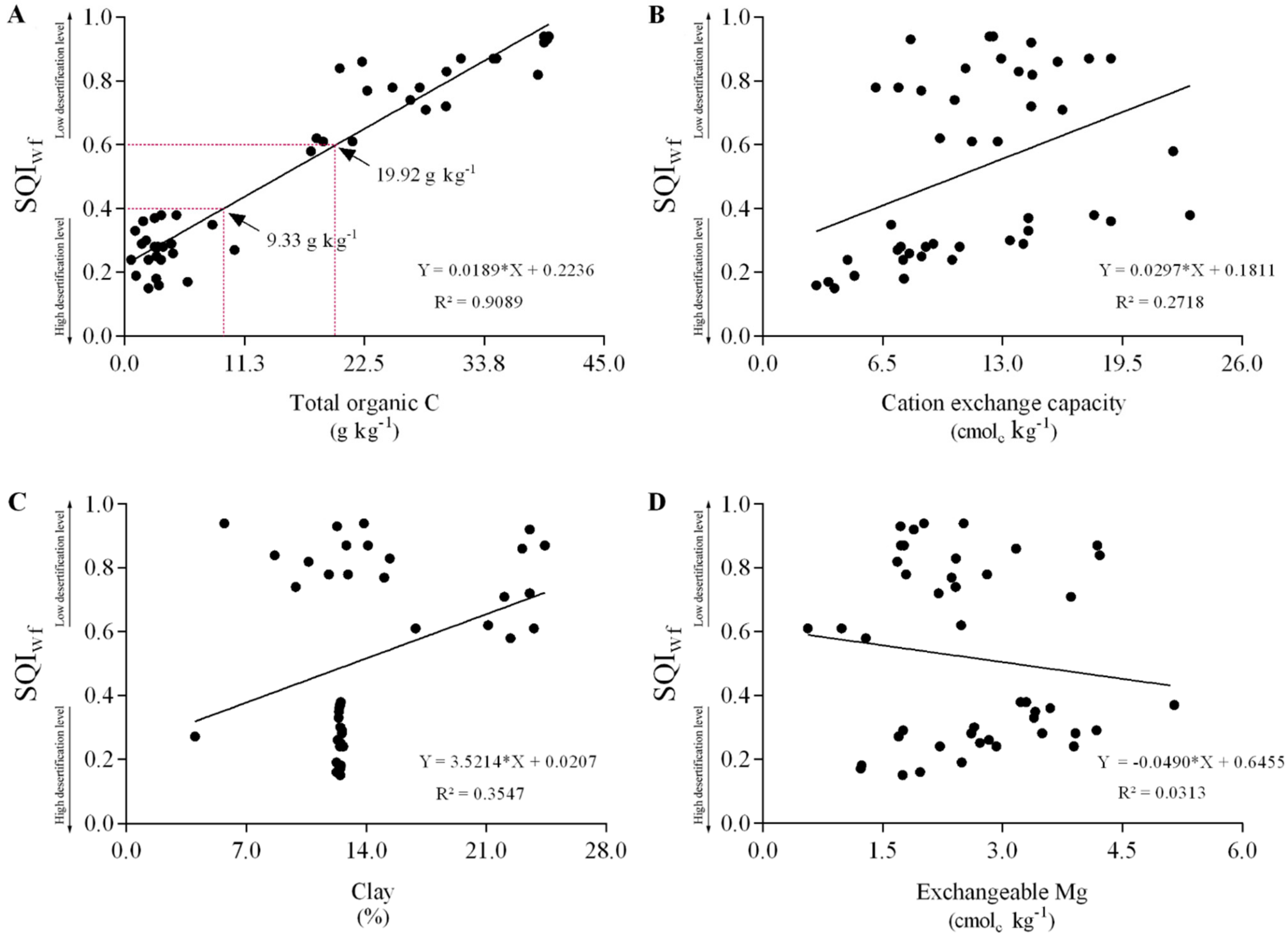


Figure 6. Relationship between the weighted factorial additive soil quality index (*SQI_{wf}*) [49] and the non-linear scores and minimum set of biophysical indicators, as selected by principal component analysis (PCA): (**A**) Total Organic Carbon in the soil; (**B**) coil cation exchange capacity; (**C**) soil clay; and (**D**) soil exchangeable Mg^{+2}. * Significant, in accordance with linear regression analysis (p < 0.05).

In this context, we used this indicator to estimate the desertification index (DI) for the entire Brazilian semiarid region. We did so in an exploratory manner, considering the limitations of the variability of soils, vegetation, and climates, and this was achieved using the digital map of organic carbon in the Brazilian semiarid region. Next, we explored correlations between the NDVI (obtained from the Instituto Nacional do Semiárido (INSA/WebGIS)) and the aridity index (AI) [61,62], both from the Brazilian semiarid region. In this exercise, we observed that the soil's TOC showed a 0.97 positive correlation with the AI. Moreover, the desertification index, obtained from the soil's TOC, reached a correlation of 0.70 with the NDVI (Figure 7). In areas with a high DI, losses related to the TOC, compared with those that had a low DI (conserved areas), were higher than 70%. In areas with a moderate DI, these losses ranged between 50% and 25%. The Brazilian Ministry for the Environment has already recognized the most degraded areas (9% of the Brazilian Semiarid Region) as nuclei of desertification; however, more studies are needed to verify these results.

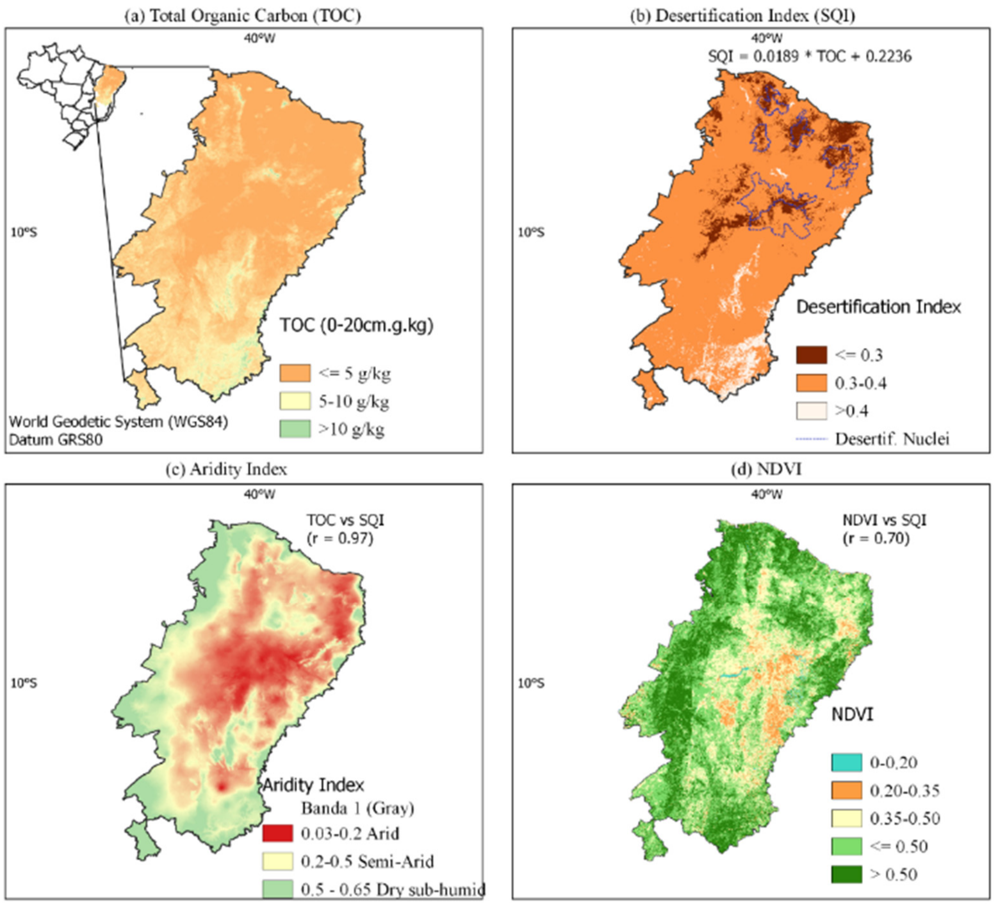


Figure 7. Maps of (**a**) Total Organic Carbon in the soil (TOC); (**b**) Desertification Index (DI); (**c**) Aridity Index (AI); and (**d**) Normalized Difference Vegetation Index (NDVI). These maps represent the indices for the entire Brazilian semiarid region.

4. Discussion

Using the present research, we were able to identify the main biophysical indicators for the characterization of desertification in the studied pilot sites, and we were also able to determine its level of desertification or conservation. In this sense, we verified that the models of regression for the calculated desertification index (DI) and MDS (TOC, CEC, Mg^{2+}, and clay) consistently indicated that the TOC was the best indicator (R^2 = 0.999) to determine the conditions of degradation or conservation of the 44 analyzed areas (Figure 6).

We observed that the areas with TOC $\geq$ 20 g kg^{-1} had low desertification indices (DI or high SQI > 0.6), whereas areas with TOC $\leq$ 9.5 g k^{-1} had high desertification indices (Figure 7). Similar results have been reported in other studies, demonstrating high soil carbon losses in areas where vegetation coverage was removed [17,18,33,34,63–65]. It is important to emphasize that the soil carbon concentration alone cannot be used as a single variable to identify areas that are susceptible to desertification, as information pertaining to the carbon concentration in soil must be combined with information concerning vegetation growth in previous rainy seasons [23–25]. Some soil types, when annually cultivated by crops, may present soil carbon levels lower than 9.5 g kg^{-1}; however, they may also remain productive and support vegetation growth during the rainy season [17]. These areas would not be considered desertified, given the criteria concerning previous vegetation growth [15,17,65]

The low levels of TOC in the soil in areas with high DI are associated with low vegetation coverage [27,36,50,66]. Areas with high DI showed a low diversity of species (1 to 4 species in 100 m^2) and a low absolute density (895 individuals ha^{-1}). In contrast, areas with a low DI showed high diversity (from 5 to 17 species) and high absolute density

(4845 individuals ha^{-1}) [6,8,36,65]. The most degraded areas (high DI) have, in general, soils with low levels of nutrients, especially P and N, due to low levels of organic carbon in the soil [17,36]. With the suppression of vegetation and the low capacity for producing greenery after rainfall, the remnants of organic matter in the uncovered soil are quickly mineralized. This process intensifies the course of desertification since organic matter is an essential component for the productivity of these soils [8,15,18,66]. The organic matter in soil controls a set of critical properties and functions that are particularly associated with nutrient availability [67,68], such as the retention of cations [69], complexation of toxic elements and micronutrients [70,71], aggregate stability [72], aeration [73], infiltration, retention of water, and microbial activity [74,75].

Visually, areas with high desertification (Figure 7) are characterized as large, denuded spots, with or without creeping vegetation cover, and they have clear signs of soil erosion [8,11]. The desertification process in these areas usually begins with the deforestation and substitution of native vegetation by crops that are different sizes, and undergo different life cycles [5,7,17]. As a result, herbaceous grasslands or short cycle crops replace the predominant shrub and tree vegetation of the Caatinga in the Brazilian semiarid region. To worsen matters further, a continuous cropping system without nutrients repositions itself after harvesting, and most of the time, this system is combined with livestock overgrazing on the herbs and shrubs, which leads to loss of soil fertility and hinders vegetation growth [8,10,49,76,77].

Furthermore, we can state that a significant part of the Brazilian semiarid region has its natural resources degraded by the current agricultural and livestock production systems [8]; thus, the desertification in the Brazilian semiarid region is similar to other regions on Earth where human actions are the main causes of such desertification [23,24,78,79]. Under these circumstances, until intervention measures are taken, desertification will continue to increase, in terms of both scale and severity. The integration and concatenation of environmental, territorial, property, and urban public policies are essential to prevent the advancement of the desertification process without any dissipation of resources. There is a current contradictory and counterproductive scenario in which progressive environmental policies often compete with public incentives to overuse vegetation strata and soils that are not capable of responding to those productive inputs, resulting in environmental degradation.

Parallel to this, the monitoring of areas where the environmental quality is undergoing a severe degradation process should receive particular attention from the government, since productive territories are being lost for present and future generations. A possible monitoring strategy could be associated with the development of a remote sensing modeling protocol that evaluates the organic carbon levels in soil across the region. The use of spectrometric techniques [79–81], in association with multiple linear regression algorithms that concern the organic carbon content of the soil [82–85], could facilitate the monitoring and systematic quantification of desertification in space–time; this would subsequently enable the adoption of relevant measures to reverse this phenomenon. Recent studies have obtained consistent results in the mid-infrared spectral range (MIR, 4000–600 cm^{-1}) for various soil attributes, such as mineralogy, clay fraction, organic carbon, and base saturation [86,87]. Such information can be used for the monitoring of desertification processes, and it could be used alongside other techniques, such as the optimal desertification monitoring index based on feature space models on a regional scale [23,24]. It is very likely that each specific region will present differences regarding the minimum set of biophysical indicators, depending on the environmental characteristics relating to that area's soil and vegetation; however, we believe that the present study points to a potentially useful methodological approach that will lead to a feasible desertification monitoring system in NE Brazil, and with the necessary adjustments, in other dry ecosystems around the globe.

5. Conclusions

The Total Organic Carbon (TOC), Clay content, Cation Exchange Capacity (CEC), and Magnesium (Mg^{2+}) contents in soil comprised the minimum set of indicators that were used to estimate the desertification index (DI) of the pilot sites in semiarid NE Brazil. Of the minimum set of biophysical indicators assessed in this study, the TOC of soil had the best performance in terms of its ability to ascertain the intensity of the desertification process; however, this was limited to those sites that presented no vegetation growth during the previous rainy seasons. Based on these findings, we believe that, in the future, the combination of modeling, orbital remote sensing information, and a small set of biophysical indicators may lead to a more effective information system that can monitor desertification. This suggested approach could supply objective, quantitative data to decision-makers regarding the need for measures that will reduce or reverse desertification processes in the dry tropical ecosystem of NE Brazil, and perhaps in other arid regions around the globe.

Author Contributions: Conceptualization, A.M.P.-M.; Data curation, J.V.; Formal analysis, J.R.Z.-S. and H.A.D.A.Q.; Investigation, J.V.; Methodology, A.M.P.-M.; Resources, A.M.P.-M.; Writing—original draft, A.M.P.-M.; Writing—review and editing, R.S.C.M., J.V., D.L.M., J.R.Z.-S. and I.M.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received external funding: Studies and Projects Funding (FINEP) for financial support (agreement N° 01.13.0345.00) and the National Observatory of Water and Carbon Dynamics in the Caatinga Biome—NOWCDCB, supported by FACEPE (grants: APQ-0296-5.01/17; APQ-0498-3.07/17 458 ONDACBC; APQ-0532-5.01/14), CNPq (grants: 441305/2017-2; 465764/2014-2), and CAPES (grants: 88887.136369/2017-00).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We wish to thank the National Institute of the Semi-Arid (INSA-MCTIC), the partnership with Federal University of Paraíba (UFPB), and Studies and Projects Funding (FINEP) for financial support (agreement N° 01.13.0345.00). This work is part of the National Observatory of Water and Carbon Dynamics in the Caatinga Biome—NOWCDCB, supported by FACEPE (grants: APQ-0296-5.01/17; APQ-0498-3.07/17 ONDACBC; APQ-0532-5.01/14), CNPq (grants: 441305/2017-2; 465764/2014-2) and CAPES (grants: 88887.136369/2017-00).

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Table A1. Normalized Difference Vegetation Index (NDVI) during the rainy season in desertified areas of the semi-arid region of Paraíba State, from 1999/2000, 2009/2010 and 2015.

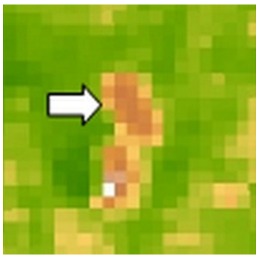
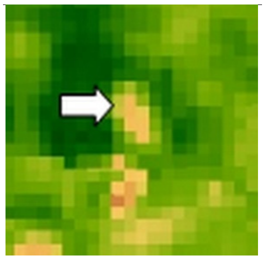
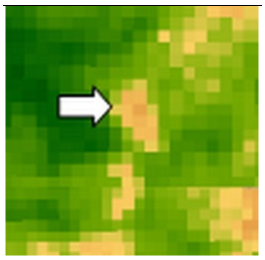
Desertified Area	Year		
	1999/2000	2009/2010	2015
1			

Table A1. *Cont.*

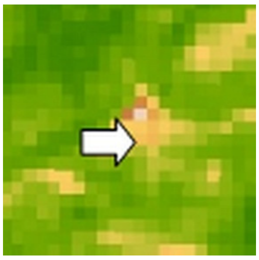
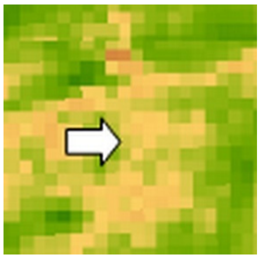
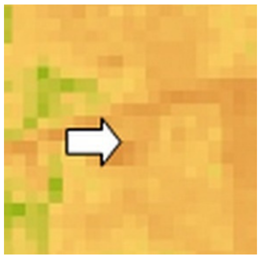
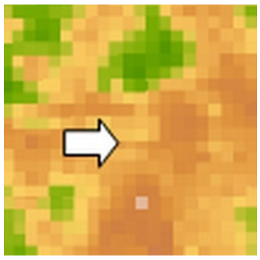
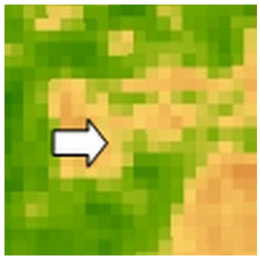
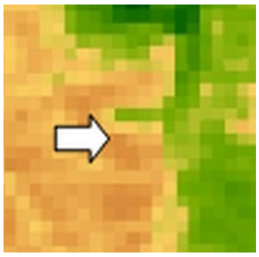
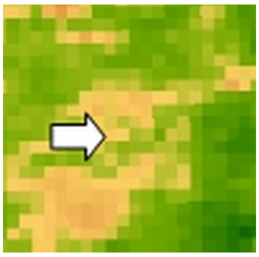
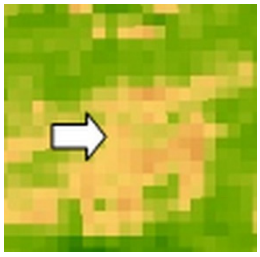
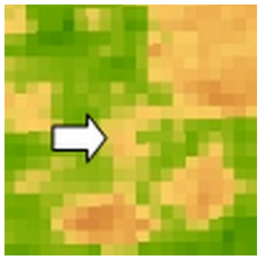
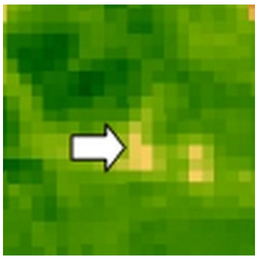
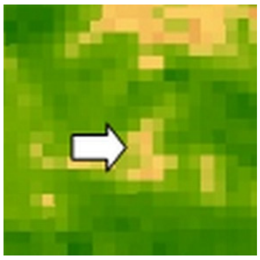
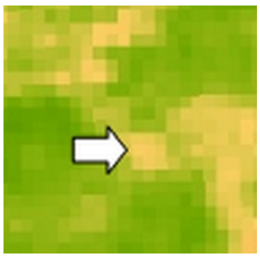
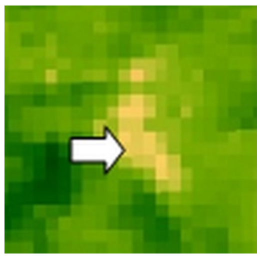
Desertified Area	Year		
	1999/2000	2009/2010	2015
2			
3			
4			
5			
6			
7			

Table A1. *Cont.*

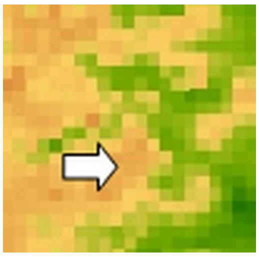
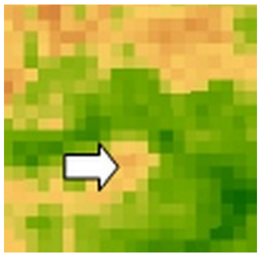
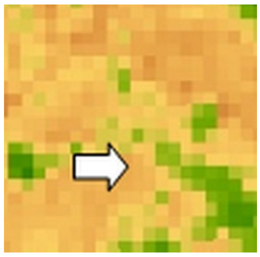
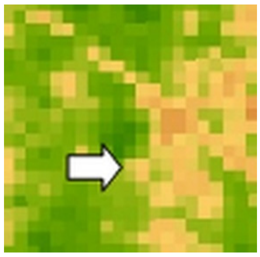
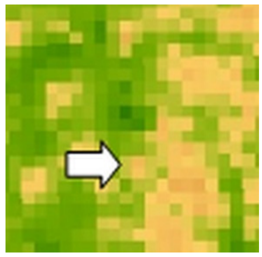
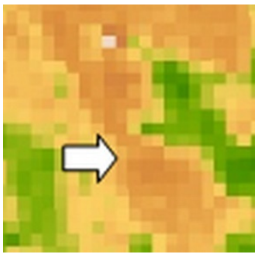
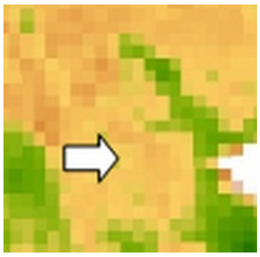
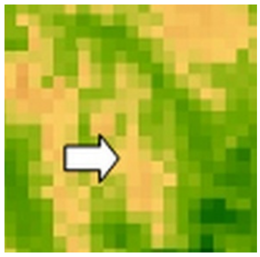
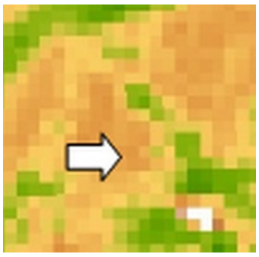
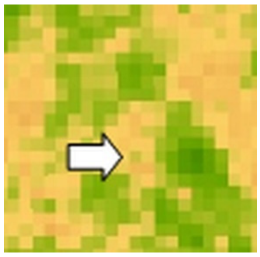
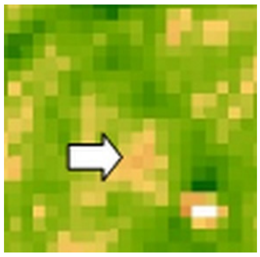
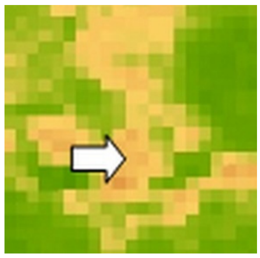
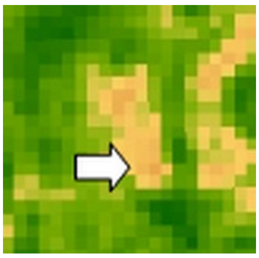
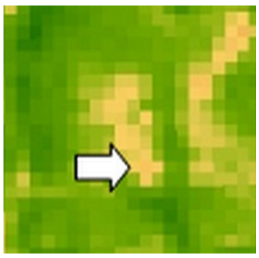
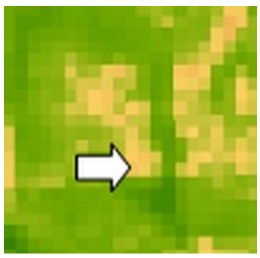
Desertified Area	Year		
	1999/2000	2009/2010	2015
8			
9			
10			
11			
12			
13			

Table A1. *Cont.*

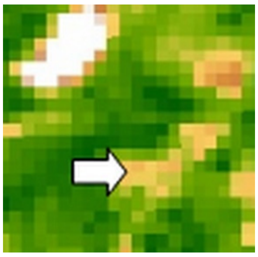
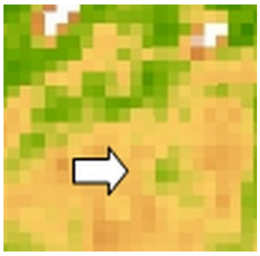
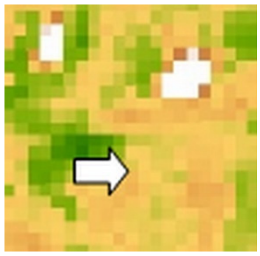
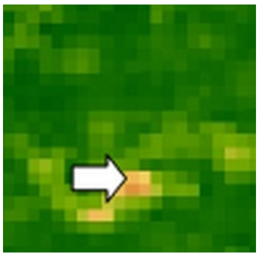
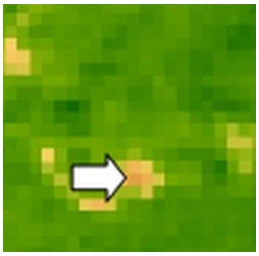
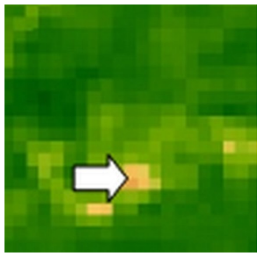
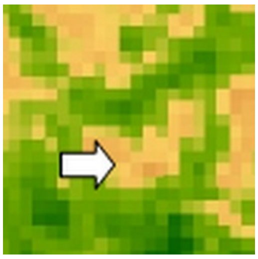
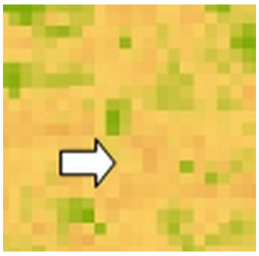
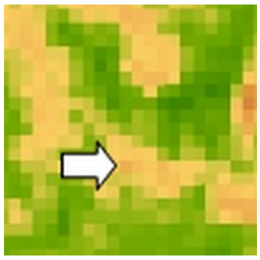
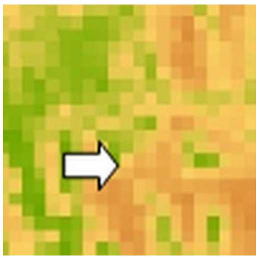
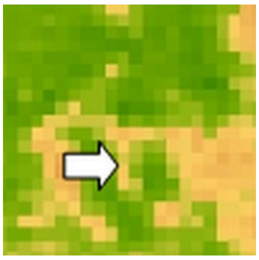
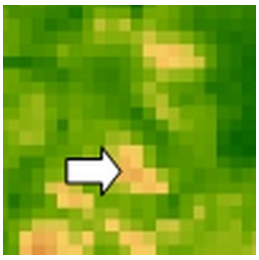
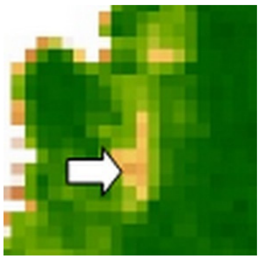
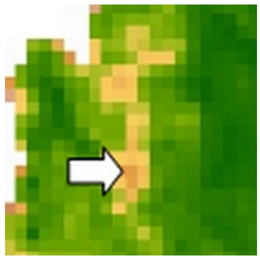
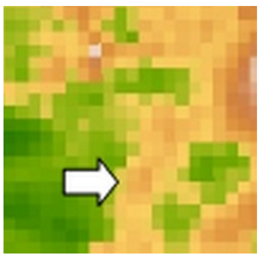
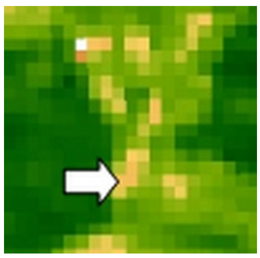
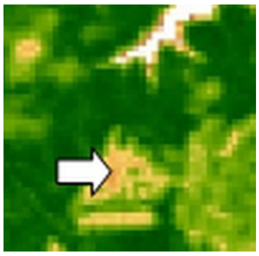
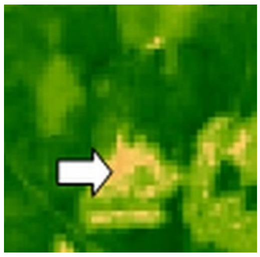
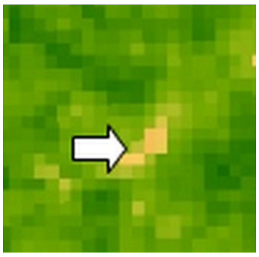
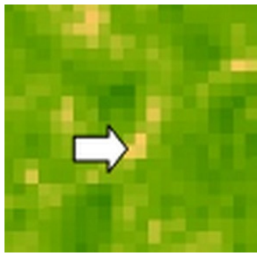
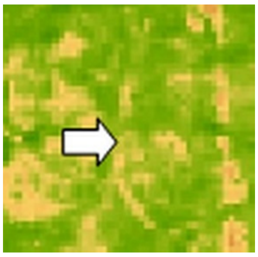
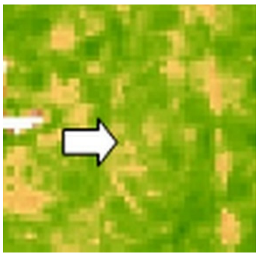
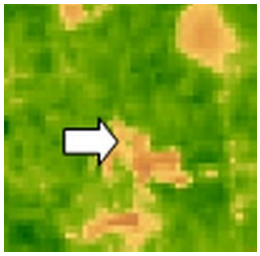
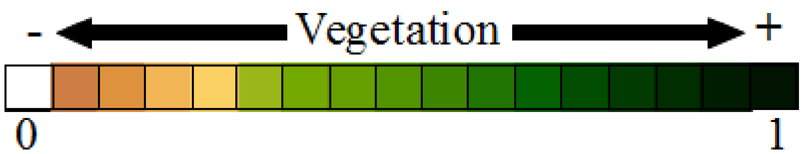
Desertified Area	Year 1999/2000	2009/2010	2015
14			
15			
16			
17			
18			
19			

Table A1. *Cont.*

Desertified Area	Year 1999/2000	2009/2010	2015
20			
21			
22			



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