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COMPARATIVE ANALYSIS OF POTENTIAL SOIL DEGRADATION IN THE STATE OF SERGIPE

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ANÁLISIS COMPARATIVO DE LA DEGRADACIÓN POTENCIAL DEL SUELO EM EL ESTADO DE SERGIPE

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RESUMO

Realizar estudos de campo para avaliar a degradação do solo é caro e demorado. Estimativas feitas por modelos numéricos são, portanto, geralmente preferidas por muitos pesquisadores e profissionais que trabalham com o assunto. O presente estudo tem como objetivo principal avaliar o estado de potencial degradação do solo (PDS) no estado de Sergipe, Brasil, nos anos de 2000 e 2019, empregando a lógica fuzzy em um ambiente de Sistema de Informações Geográficas (SIG). O modelo proposto explora relações de causa-efeito entre variáveis específicas que são conhecidas por afetar o PDS, com base em funções de pertinência e o Operador Gama Fuzzy (OFG) aplicado a dados relativos a geologia, geomorfologia, declividade, hipsometria, pedologia, precipitação, erodibilidade, índice de vegetação melhorado (IVM) e uso da terra. Nossos resultados mostram que, dentre esses fatores, os que mais contribuíram para a degradação foram a geologia, geomorfologia, pedologia e precipitação. No entanto, a devida atenção deve ser dada às variáveis suscetíveis a mudanças na escala de tempo humana, como precipitação, uso e cobertura do solo e, consequentemente, o IVM, que se mostraram importantes contribuintes para o aumento observado da PDS ao longo do tempo estudado. Desses, principalmente, o uso e cobertura da terra, por se tratar de uma variável intimamente relacionada às atividades humanas. Os produtos cartográficos resultantes deste trabalho, indicam as regiões que apresentam os fatores mais e menos importantes no que diz respeito à influência nos processos que contribuem para a degradação do solo, mostrando-se uma ferramenta valiosa para a gestão sustentável do ambiente.

Palavras-chave: Geoprocessamento; lógica Fuzzy; meio ambiente; sensoriamento remoto; análise temporal.

ABSTRACT

Performing field studies to assess soil degradation is expensive and time-consuming. Estimates made by numerical models are, therefore, usually preferred by many researchers and professionals that work on this subject. The present study primarily aims to assess the potential soil degradation (PSD) in the state of Sergipe, Brazil, in the years 2000 and 2019, by employing the fuzzy logic in a Geographic Information System (GIS) environment. The proposed model explores cause-effect relationships between specific variables that are known to affect the PSD, based on membership functions and the Fuzzy Gamma Operator (FGO) applied to data relative to geology, geomorphology, declivity, hypsometry, pedology, precipitation, erodibility, enhanced vegetation index (EVI) and land use. Our results show that, among these factors, the ones that most contributed to degradation were geology, geomorphology, pedology and precipitation. However, proper attention should be paid to variables susceptible to changes in the human timescale, such as precipitation, land use and cover and, consequently, the EVI, which were found to be important contributors to the observed increase in PSD along the studied timespan. Of those, especially, land use and cover, as it is a variable closely related to human activities. The cartographic products resulting from this work are also successful in indicating the regions that exhibit the most and the least important factors with respect to the influence on the processes that contribute to soil degradation, proving to be a valuable tool for decision-making in the planning of preventive and mitigating measures.

Keywords: Geoprocessing; Fuzzy logic; environment; remote sensing; temporal analysis.

RESUMEN

La realización de estudios de campo para evaluar la degradación del suelo es costosa y requiere mucho tiempo. Por lo tanto, las estimaciones hechas por modelos numéricos son generalmente preferidas por muchos investigadores y profesionales que trabajan en el tema. El presente estudio tiene como objetivo principal evaluar el estado de degradación potencial del suelo (PDS) en el estado de Sergipe, Brasil, en los años 2000 y 2019, utilizando lógica difusa en un entorno de Sistema de Información Geográfica (SIG). El modelo propuesto explora relaciones causa-efecto entre variables específicas que se sabe que afectan el PDS, basado en funciones de membresía y el Operador Gamma Difuso (OFG) aplicado a datos relacionados con geología, geomorfología, pendiente, hipsometría, pedología, precipitación, erosionabilidad, índice de vegetación mejorado (IVM) y uso de la tierra. Nuestros resultados muestran que, entre estos factores, los que más contribuyeron a la degradación fueron la geología, la geomorfología, la pedología y la precipitación. Sin embargo, se debe prestar la debida atención a las variables susceptibles de cambios en la escala de tiempo humana, como la precipitación, el uso y la cobertura del suelo y, en consecuencia, el IVM, que han demostrado ser importantes contribuyentes al aumento observado en el PDS a lo largo del tiempo. estudió. De estos, principalmente, el uso y cobertura del suelo, por ser una variable muy relacionada con las actividades humanas. Los productos cartográficos resultantes de este trabajo señalan las regiones que presentan los factores más y menos importantes en cuanto a la influencia sobre los procesos que contribuyen a la degradación del suelo, demostrando ser una herramienta valiosa para la gestión sostenible del medio ambiente.

Palabras-clave: Geoprocesamiento; lógica difusa; medio ambiente; detección remota; análisis temporal.

INTRODUÇÃO

The environment is always undergoing dynamic processes due to the several sources and sinks of matter and energy inherent to the systems that it comprises. Owing to anthropogenic interventions, whether direct or indirect, or to natural variability, the environment can face varied levels of degradation, which can also affect the living beings that depend on it. Chopra (2016), defines environmental degradation as the deterioration of the environment through the consumption of natural resources such as air, water, and soil, accompanied by the destruction of natural systems and the eradication of wildlife. The main causes of environmental degradation are modern urbanization, industrialization, overpopulation, deforestation, etc. One of the most frequent forms of degradation is environmental pollution, which refers to a negative change in the quality and quantity of natural resources.

Machado (2012) asserts that the degradation in Brazil began with the deforestation that took place in the Northeast, for the extraction of Paubrasilia echinata (locally known as pau-brasil). The degradation of the native vegetation cover in the region accelerated with the cultivation of sugarcane and, later, with cattle raising. Such processes have an immediate effect on the soil and its properties.

As stated in Lal (2015), soil degradation is characterized by the loss of the quality of its ecosystem services, since the soil is a non-renewable resource in the human time scale, with its vulnerability to degradation depending on complex interactions between processes, factors and causes that occur in different spatial and temporal scales. Soil degradation is a 21st century global problem that is especially severe in the tropics and sub-tropics. Some estimates indicate degradation decreased soil ecosystem services by 60% between 1950 and 2010 (Leon e Osorio, 2014). Among the main soil degradation processes are erosion, depletion of soil carbon stock, loss of biodiversity, loss of fertility, chemical imbalance, acidification, and salinization.

Fernandes and Medeiros (2009) affirm that, owing to its limiting characteristics for some agro-pastoral activities, which, in turn, led to deforestation and forest fires, as well as to a history of mistaken mitigating measures, the Northeast region currently faces serious environmental problems.

The state of Sergipe, which is in the Northeast of Brazil, hosts several economic activities that have the potential for soil degradation, such as agriculture, livestock, mining (of limestone, iron ore, sand, manganese, potassium, and oil). Despite being the smallest state of the country, it is home to two different biomes: Caatinga and Atlantic Forest (Mata Atlântica). At the present time, few, if any, detailed studies have addressed the important issue of soil degradation in the state of Sergipe as a whole.

Due to the often-broad spatial dimensions and diversity of aspects inherent to the environment and the interactions between its natural systems and artificial processes, environmental studies demand integration between multiple sources and kinds of information to assure that relevant characteristics are properly considered. In this regard, information pertaining to data from several fields is required, including geology, geomorphology, pedology, land use and cover, and climate (e.g., temperature and precipitation), among possibly others. By enabling such a holistic approach, the geotechnologies are proving to be very useful for studies in this field. Geographic Information Systems (GIS) can be used to obtain, analyze, and relate spatial and temporal data of a specific area, though, e.g., statistical techniques and map algebra, enabling scientists to perform a diagnosis of the regions that are most susceptible to environmental problems. Through remote sensing, it is possible to assess several physical, chemical, and biological parameters on a large scale from instruments of different purposes onboard of satellites orbiting the Earth, without the need for an in situ visit to collect data.

Among the techniques used to handle data from different sources in a combined fashion, is the fuzzy logic. The theory of Fuzzy Sets and the concepts of the fuzzy logic, conceived by Zadeh (1965, 1978) have been widely applied because of the intrinsic potential for a mathematical analysis of non-discreet processes and natural phenomena that take place in the environment. Pourghasemi et al. (2012) state that the fuzzy logic is objective and straightforward to understand and implement. The method allows the use of data in any scale, with the assignment of weighting being entirely controlled by the researcher.

The fuzzy logic allows, depending on the function being used to relate the elements, establishing different degrees of association between them. The degree quantified for those values are also known as grade of membership, degree of compatibility or degree of truth. According to Sema et al. (2017), values 0 and 1 denote minimum and maximum influence of a particular factor on a given phenomenon, respectively. Conforming to Çakiy and Karwowski (2018), fuzzy overlay can be selected as tool in GIS-based methodologies because it is particularly well suited for continuous data, difficult to define, or derived from expert opinion. That is, it has the capability to model vagueness and ambiguity in complex systems, like natural process occurred in the environment. Sema et al. (2017) stresses that different operators can be employed to combine the membership values of two or more thematic maps from a fuzzy function. Raines et al. (2010), indicate the use of five fuzzy operators, are they, fuzzy AND, fuzzy OR, fuzzy SUM, fuzzy Product and fuzzy gamma operator

(FGO), that can provide different aspect of data membership to the multiple input criteria. Among them, a convenient operator type should be selected according to the desired outcomes of the final map.

Fuzzy "AND" is equivalent to a Boolean AND (intersection), with the resulting membership values being controlled by the minimum values of the input data. Fuzzy "OR" works identically to the Boolean OR (union). In this case, the resulting membership values are controlled by the maximum values among those coming from the input data. The fuzzy Product is defined as the product of the resulting values of the membership functions relating the n fuzzy sets to be combined. The Algebraic Sum is the mathematical complement of the algebraic product. Then, the FGO is defined as the product between the Algebraic Sum and the Algebraic Product. In an FGO, there is a Gamma (γ) exponent, a parameter whose value is chosen between 0 and 1. When $\gamma = 1$, the combination is the same as the Algebraic Sum. Conversely, when $\gamma = 0$, the combination is equivalent to the Algebraic Product. Lee (2007) argues that a thoughtful choice of γ generates results that guarantee a flexible balance between the "increase" propensity of the Algebraic Sum and the "decrease" tendency that is natural to the Algebraic Product.

In agreement with Vieira et al. (2014), a fuzzy system is a function of n real numbers, built through a specific methodology according to 3 modules. The first module is the fuzzification, which mathematically models the information from each input variable through fuzzy sets. It is in this stage that the major role of expert (in the process to be analysed) becomes evident, as each input variable is assigned linguistic terms that represent the states of the variable, and each linguistic term must be associated with a fuzzy set through a membership function. Therefore, it is in this module that the variables and their linguistic classifications are stored.

The second module is the one of inference: this is where logic connectives used to establish the fuzzy relation that models the base of rules are defined. The success of the fuzzy system depends primarily on this module, since it will provide the fuzzy output (control) to be adopted by the controller from each fuzzy input. The third module is defuzzification, which translates the state of the fuzzy output variable to a numerical value.

The method of fuzzy logic allows weighted combinations of maps and can be quickly implemented in a GIS environment (Pradhan 2010). There are some precedents in literature as to the use of fuzzy logic implemented in GIS to perform environmental studies, e.g., Pourghasemi et al. (2012); Silva et al. (2013); Silva Junior (2015); Bortoloti et al. (2015); Amirahmadi et al. (2017); Sema et al. (2017); Jagabandhu and Saha (2019); Haidara et al. (2019).

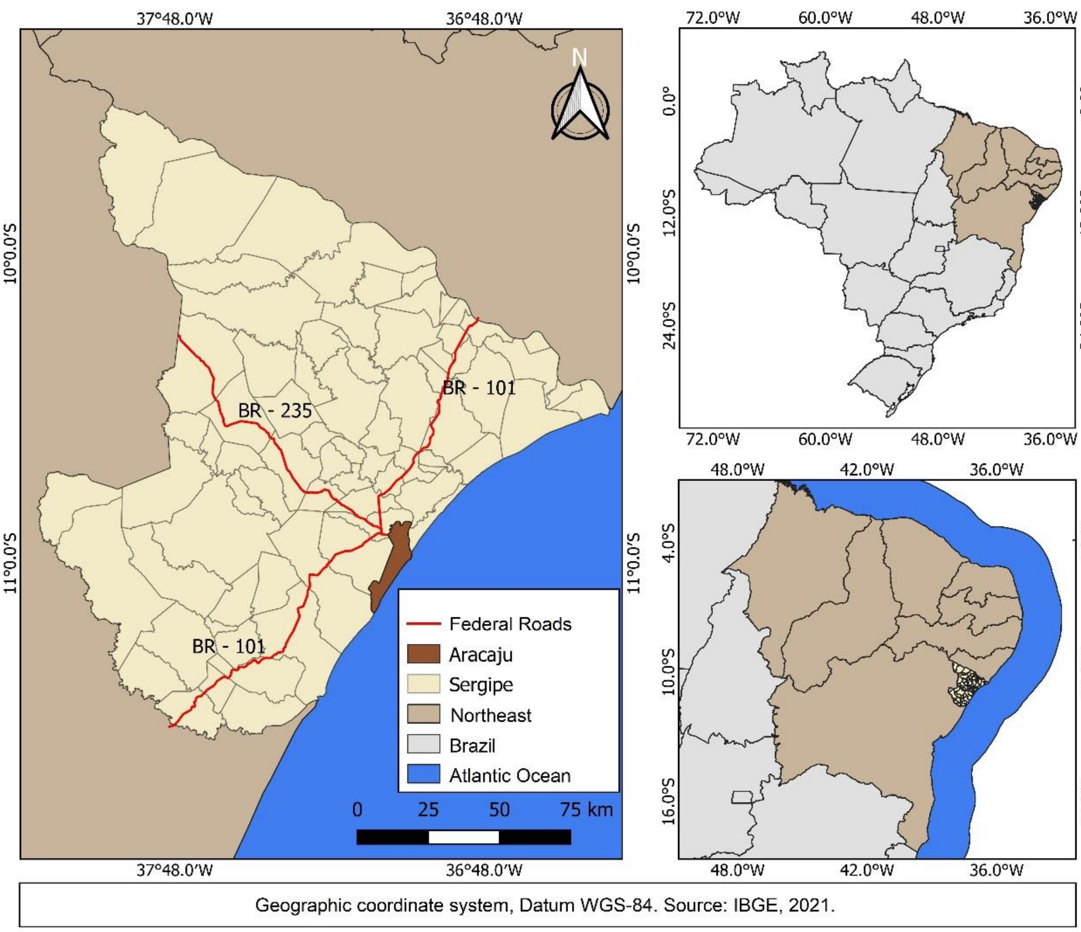
The present study has the overall aim of comparing the situation of the potential soil degradation (PSD) in the state of Sergipe in the year 2000 with the one of 2019, using fuzzy logic in a GIS environment. In the process of accomplishing this, a fundamental step was the producing thematic maps of PSD through the application of geoprocessing and statistical techniques, so that could be visually identify areas with higher/lower potential for soil degradation, and thus assess the characteristics of the local landscape and their individual contributions to the observed environmental degradation of the soil.

MATERIAL AND MATHODS

Study Area

According to the Brazilian Institute of Geography and Statistics (IBGE, 2019), the state of Sergipe comprises an area of 21,926.908 km^2 and is inhabited by 2,298,696 people (2019 estimate). Figure 1 presents a location map for the state of Sergipe, in which it is highlighted in relation to the Northeast region of Brazil and the whole country.

Figure 1. Location map of the state of Sergipe. Source: created from the Digital Atlas of Water Resources (SEMARH, 2014).

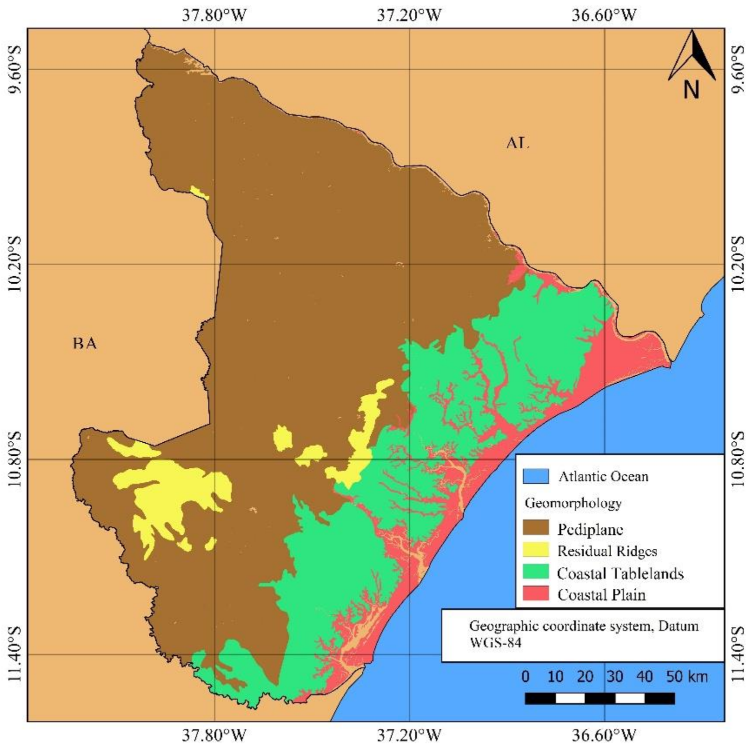


Source: Digital Atlas of Water Resources (SEMARH, 2014). Org. Barros, 2021.

Regarding its climate, as stated in Diniz et al. (2014), the precipitation amounts decrease from the coast to the interior, to the extent that the southeast coast exhibits only 0 to 2 dry months, whereas the northwest undergoes a dry period that lasts from 7 to 8 months. The predominant climatic types are as follows: humid climate prevails especially in the "Zona da Mata" region, in the coastal "tabuleiros" (tablelands); a sub-humid characterizes the transition zone, locally known as "Agreste", consisting of 3-6 dry months; the semi-arid climate (7-8 dry months) occurs in the interior portion, where there are pediplains and residual ridges (Mendonça and Danni-Oliveira, 2007).

As to the geomorphological aspects of the state, conforming to the National Department of Transport Infrastructure (2017), the topography shows mild variations, with plain areas and modest altitudes that increase towards the interior, locally interrupted by elevations called "serras" (ridges), which constitute the highest points in the state, such as Serra Negra (750m), Serra de Itabaiana (650 m) and Serra da Miaba (500 m). Concerning the compartmentalization of the terrain, the following geomorphological units can be identified, as shown in Figure 2: The Coastal Plains; the Coastal Tablelands; the Pediplains and the Residual Ridges.

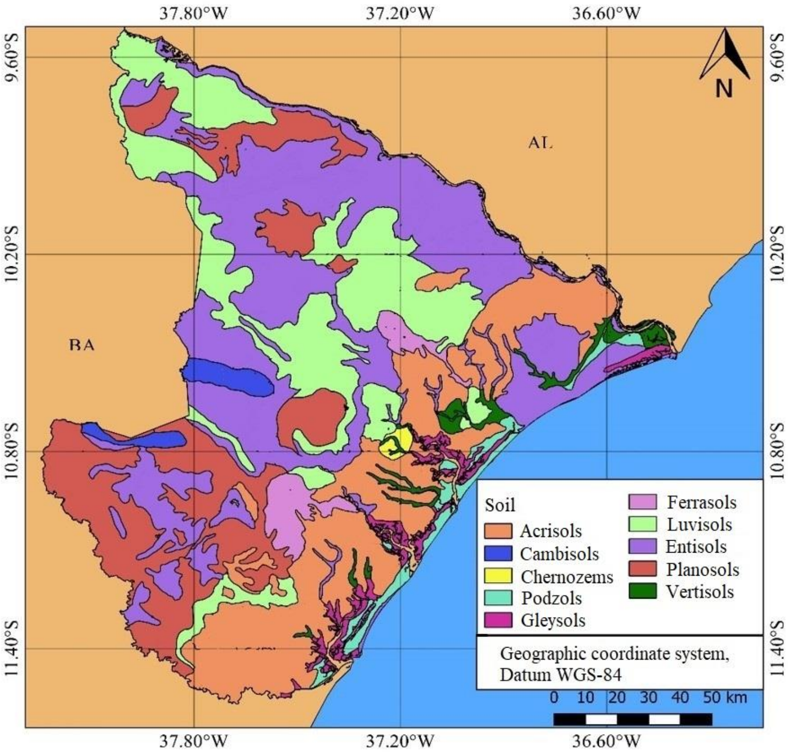
Figure 2. Geomorphological units of the state of Sergipe.



Source: Digital Atlas of Water Resources (SEMARH, 2014). Org. Barros, 2021.

Several soil types can be found across the region. According to Aragão et al. (2011), there is a greater predominance of Acrisols and quartz-rich Neosols. Figure 3 exhibits the soil taxonomy as carried out by the Secretariat for the Environment and Water Resources of the State of Sergipe (SEMARH). To elaborate the map in this Figure, the types of soil were correlated with the Food and Agriculture Organization (FAO, 2015).

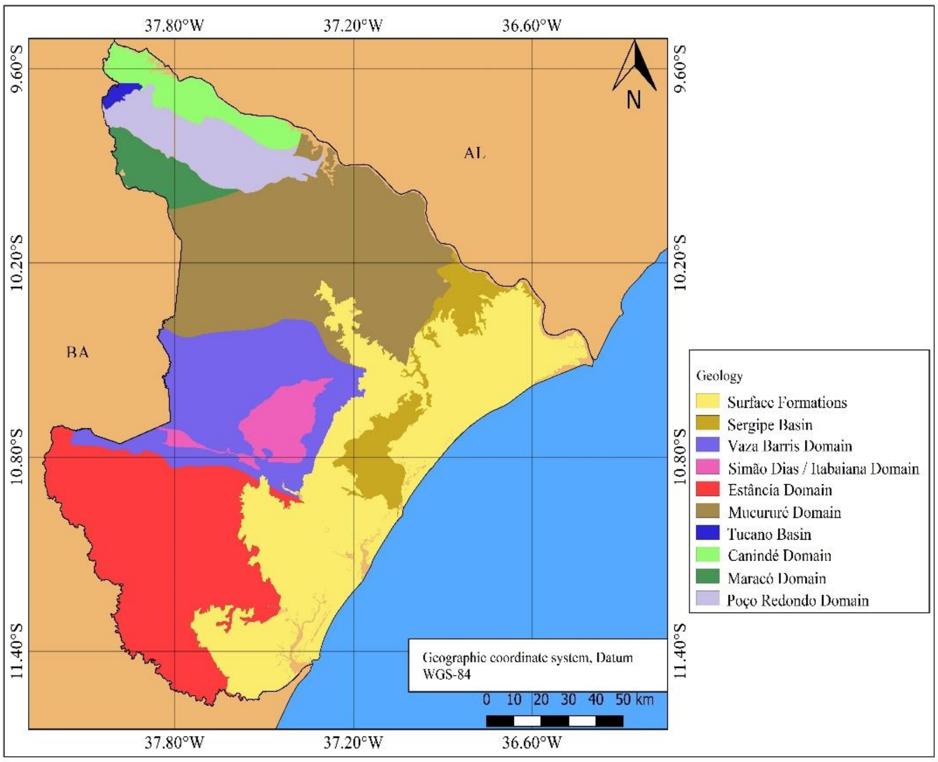
Figure 3. Soil types in the state of Sergipe.



Source: Digital Atlas on Water Resources (SEMAR/SRH, 2014). Org. Barros, 2021.

The state of Sergipe is in a boundary region between three structural provinces known as: São Francisco Province, Borborema Province and Coastal Province. The main geological formations of the state are: Poço Redondo, Marancó, Macururé, Canindé, Vaza Barris and Estância. Figure 4 showcases their spatial distribution.

Figure 4. Geological formations in the state of Sergipe.

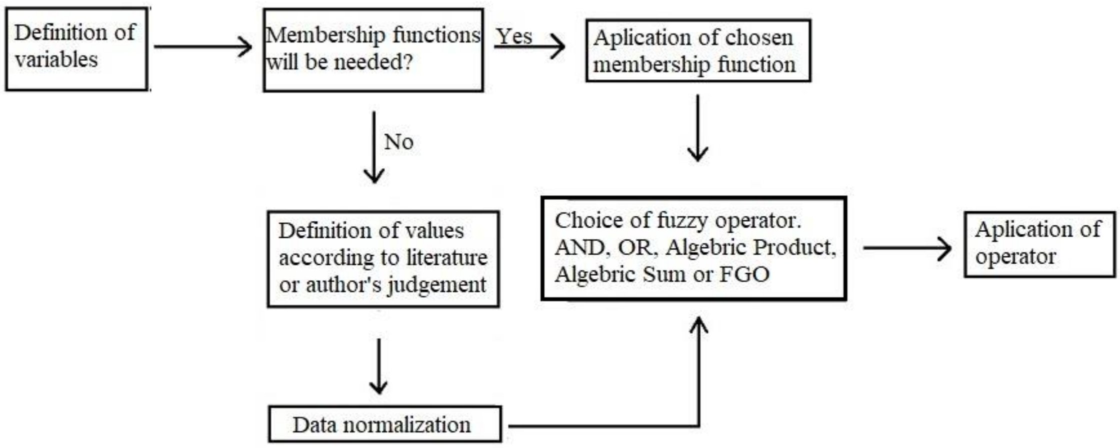


Source: Digital Atlas on Water Resources (SEMAR/SRH, 2014). Org. Barros, 2021.

Fuzzy Logic System

The construction of a model based on fuzzy logic goes through some fundamental steps (see Figure 5), such as: defining input and output variables; application of the membership functions that will perform the fuzzy inference for the conversion of the original values to the 0-1 range or performance of the assigning the values based on the literature (this is necessary because the input values can be computed from functions such as linear, sigmoidal, trapezoidal, triangular, or defined based on results of previous studies); choosing the fuzzy operator to be employed, among the options discussed above. The FGO is the operator used in this study.

Figure 5. Flowchart of the steps to produce maps of PSD.



Source: Author, 2021.

For this research, we used data from the Tropical Rainfall Measuring Mission (TRMM), the Moderate-Resolution Imaging Spectroradiometer (MODIS), MapBiomas, Projeto Topodata and SEMARH. The variables, their respective sources, the membership function applied to each one and the reference works on which the fuzzy inference are based can be found in Table 1. The sigmoidal and linear functions used here are controlled by four points, ordered from the lowest value (Pmin) to the highest (Pmax) of each variable. When the variable contributes in a directly proportional way to degradation, linear equations (Equation 1) or monotonic sigmoidal equations (Equation 2) are used as its value increases. When the variable contributes in an inversely proportional manner to degradation worsening, decreasing monotonic equations are used as its value increases. Thus, the closer to 0, the lower the contribution to soil degradation, and the closer to 1, the greater the contribution.

Table I. Variables, their respective sources and methods used for the fuzzy inference.

Variable	Source	Space resolution	Membership Function / Normalization
Precipitation	Tropical Rainfall Measuring Mission (TRMM), (2020).	0,25°	Monotonic crescent sigmoidal
Erodibility	Vector data of the Sergipe hydrographic system, SEMARH (2014).	100 m	Linear monotonic crescent
Enhanced Vegetation Index - EVI	MOD13A3 product of MODIS sensor, available Earth Data Search website (2020)	0,01°	Monotonic decreasing linear
Land and cover of soil	MapBiomas project (Souza et. al. 2020).	30 m	Canavesi et al. (2013), Roy & Saha (2019), Lee (2007), Balamurugan et al. (2016)
Slope	Data available in the Topodata Project (Valeriano 2009).	30 m	Monotonic crescent sigmoidal
Elevation	Data available in the Topodata Project (Valeriano 2009).	30 m	Monotonic crescent sigmoidal
Geology	Digital Atlas of Water Resources, SEMARH (2014).	30 m	Linear monotonic crescent
Geomorphology	Digital Atlas of Water Resources, SEMARH (2014).	30 m	Linear monotonic crescent
Pedology	Digital Atlas of Water Resources, SEMARH (2014).	30 m	Linear monotonic crescent

Source: Adapted by the authors.

The QGIS software, version 2.18.12, was used for geoprocessing and for standardizing all the information contained in the data, in raster format, seting the same spatial bounds (the state of Sergipe), temporal resolution, coordinate reference system (CRS) and Datum. Equations (1) and (2), used in the step of fuzzy inference, and Equation (3) (the FGO, as described in Nyimbili and Erden, (2020)), were implemented through the Raster Calculator plugin.

$$\mathrm{F(x)} = \frac{\mathrm{Pmin} - \mathrm{x}}{\mathrm{Pmáx} - \mathrm{Pmin}} \tag{1}$$

$$\mathrm{F(x)} = \left(\cos^2 . \frac{(\mathrm{x} - \mathrm{Pmáx})}{(\mathrm{Pmáx} - \mathrm{Pmin})} . \frac{\pi}{2}\right) \tag{2}$$

$$\mu_{combination} = \left(\prod_{i=1}^{n} \mu_i\right)^{\gamma} x \left(1 - \prod_{i=1}^{n} (1 - \mu_i)\right)^{1-\gamma} \tag{3}$$

Where x is the value of each pixel within the raster, representing each variable, μi is the result of the membership function for each raster, i = 1, 2… n is the number of rasters that make up the model, and γ is the gamma exponent. Five γ values were tested: 0.1, 0.3, 0.5, 0.7 and 0.9.

Equation (3) was first applied to data from the year 2000, for each γ value, and then to data from 2019. The results obtained through the application of the FGO were arranged in five classes of PSD, as shown in Table 2.

Table II. Classification of PSD according to FGO values

Interval	Class
0,0 – 0,2	Very low
0,2 – 0,4	Low
0,4 – 0,6	Moderated
0,6 – 0,8	High
0,8 – 1,0	Very high

Source: Adapted by the authors.

To achieve a better coherence and understanding during the interpretation of the results, some procedures were carried out:

- Calculation of the area encompassed by each class for γ = 0.5 for both 2000 and 2019.
- Linear regression between the data (after the fuzzy inference was performed) and the result attained for γ = 0.5.

Such γ value was chosen so that the effects of very pessimistic scenarios (close to 1) or very optimistic (close to 0) would not influence in the regression, thereby causing undesired and biased results. Pearson correlation coefficients (r) were then obtained through the "r.regression.line" algorithm in QGIS.

For the calculation of the areas, the "Classification Report" tool was used, from the Semi-Automatic Classification plugin in QGIS. This tool outputs a report with the amount of pixels, the area in percentage and the area in degrees squared (°2) for each class. The report is exported to a spreadsheet file. By using a spreadsheet software, it was possible to convert the area unit to hectares (ha).

The Pearson correlation coefficient (r) ranges between -1 and 1. The higher the modulus of r, the stronger the linear relationship between the variables (Martins, 2014). The relationship will be linear positive if r is positive. In this case, there is a direct correlation, i.e., the values of one variable increase as the other experiences an increase in theirs. The relationship will be linear negative if r is negative. In this case, there is an inverse correlation, i.e., the values of one variable increase (decrease) while the values of the other variable decrease (increase). Here, we adopted the correlation classes proposed by Martins (2014), displayed in Table 3.

Table III. Classification of the Correlation Intensity (CI). Source: Adapted from Martins (2014).

r values	Correlation Intensity (CI)
-1 < r ≤ -0,7	Strong negative
0,7 < r ≤ -0,5	Moderate negative
-0,5 ≤ r < 0	Weak negative
0	Null
0 < r ≤ 0,5	Weak positive
0,5 < r ≤ 0,7	Moderate positive
0,7 ≤ r < 1	Strong positive

Source: Adapted by the authors.

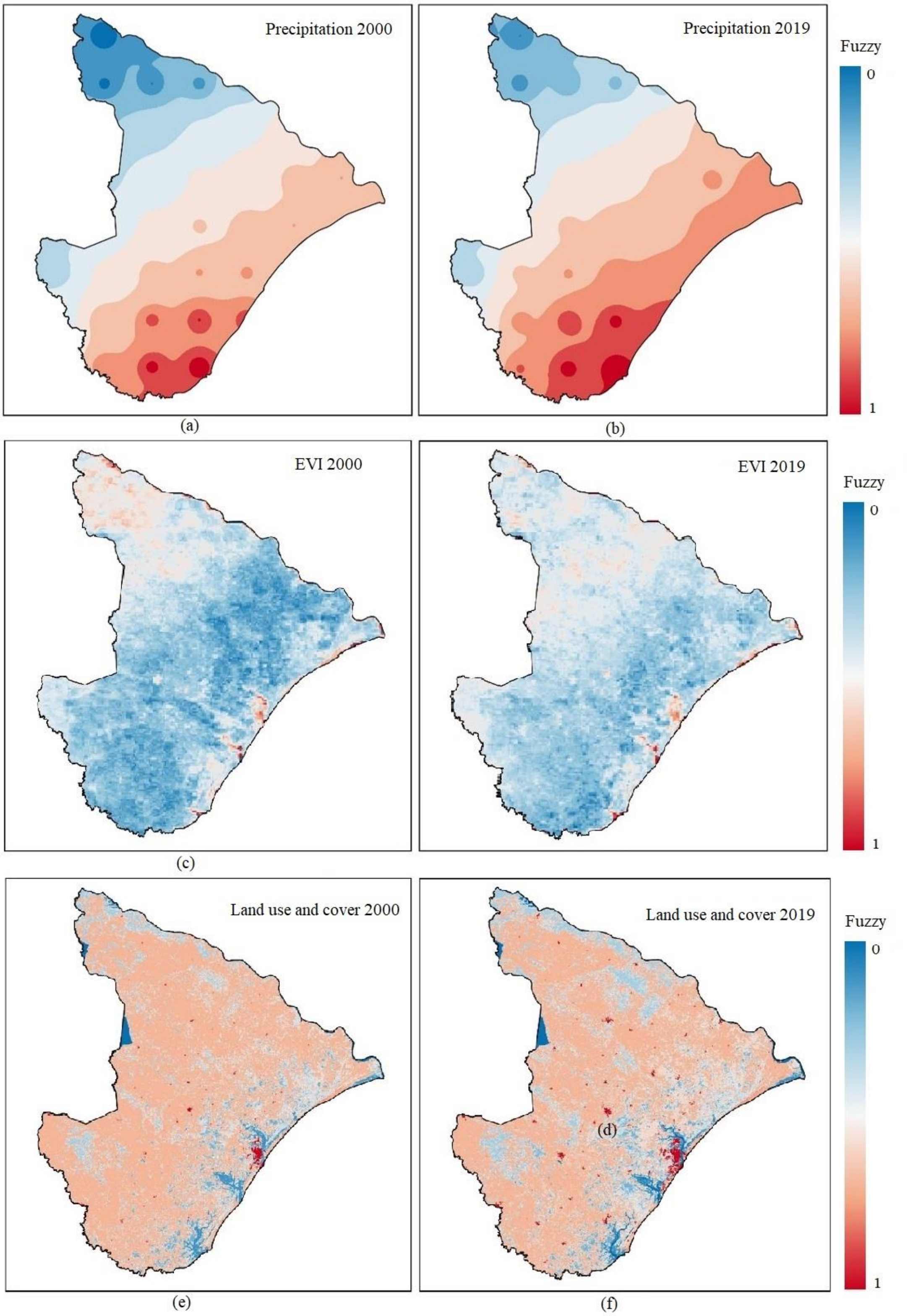
RESULTS

Figures 6 and 7 show the results of fuzzy inference performed on the input data. It is possible to see that, after the application of the inference functions, the fuzzy values behave as expected, that is, areas in which the variables bear characteristics (whether qualitative or quantitative) that contribute to an increase in the PSD are those that showed highest fuzzy values, around 1. Conversely, the areas where the variables possess properties that do not contribute to an elevation in the PSD, exhibited the lowest fuzzy values, close to 0. The influence of each variable will be fully addressed hereinafter, as well as the results of the linear regression performed, which corroborate with the other results.

Figure 6 convene the variables that are susceptible to possible significant changes in the timescale comprised by the two datasets (from 2000 to 2019), namely: precipitation, EVI and land use and cover. It is possible to observe that, for these three variables, there was an overall increase in fuzzy values, mainly in the coastal strip and in the Coastal Tablelands. Such increase indicates a greater contribution of these variables to the intensification of the PSD from 2000 to 2019.

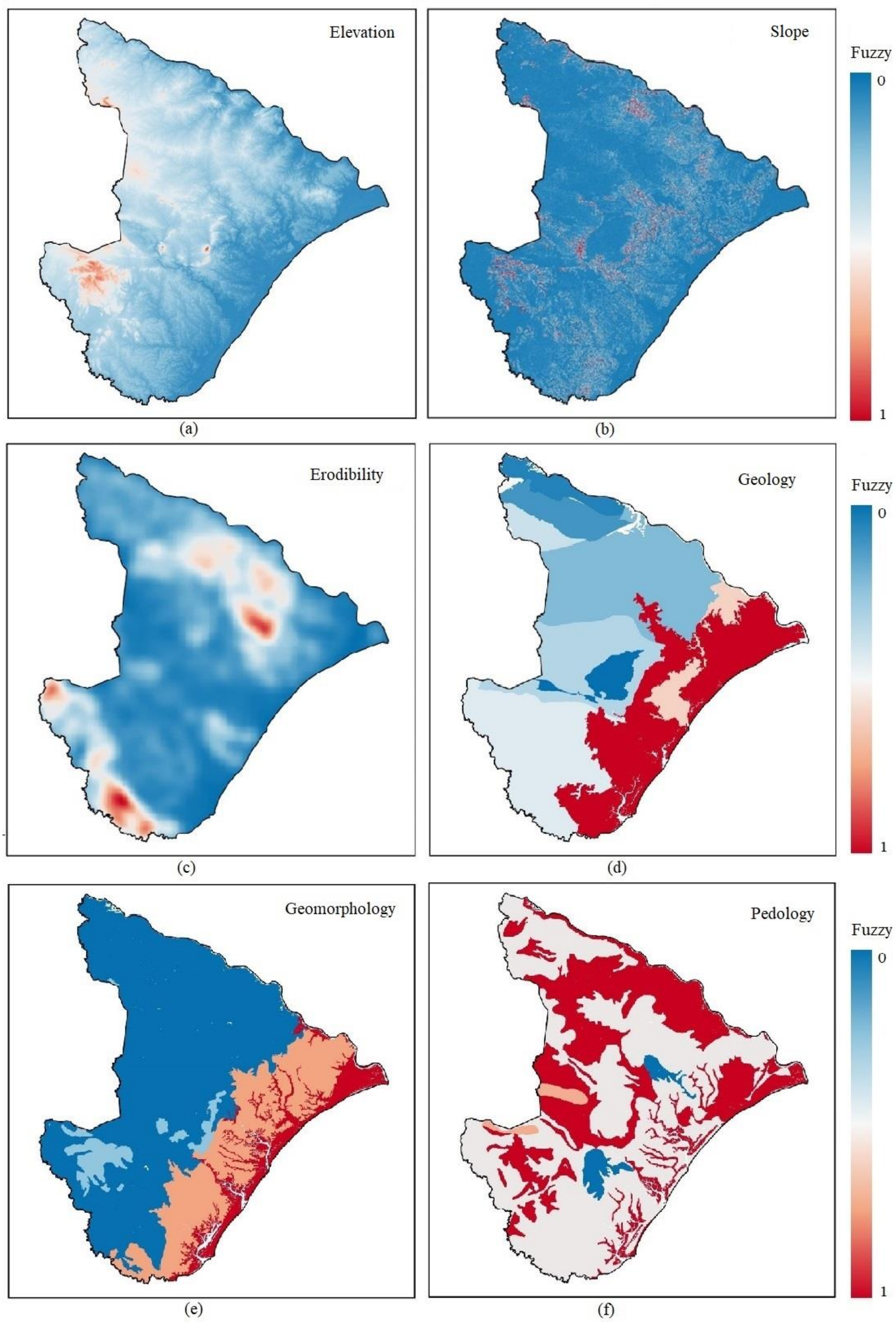
Figure 7 shows the variables whose variations occur on a timescale that exceeds the one of the human socioeconomic activities, i.e, changes that take place in the scale of thousands of years, such as geology, geomorphology, pedology, altitude, slope and erodibility. Therefore, for these variables, no comparison between results from the two years is presented.

Figure 6. Fuzzy values for the input variables: (a) average rainfall for the year 2000; (b) average rainfall for 2019; (c) average EVI for 2000; (d) average EVI for 2019; (e) land use and cover in 2000; (f) land use and cover in 2019.



Source: Author, 2021.

Figure 7. Fuzzy values for the remaining input variables as assessed for the year 2020: (a) elevation; (b) slope; (c) erodibility; (d) geology; (e) geomorphology; (f) pedology. As explained above, it is not necessary to obtain the Fuzzy values for both years for these variables.

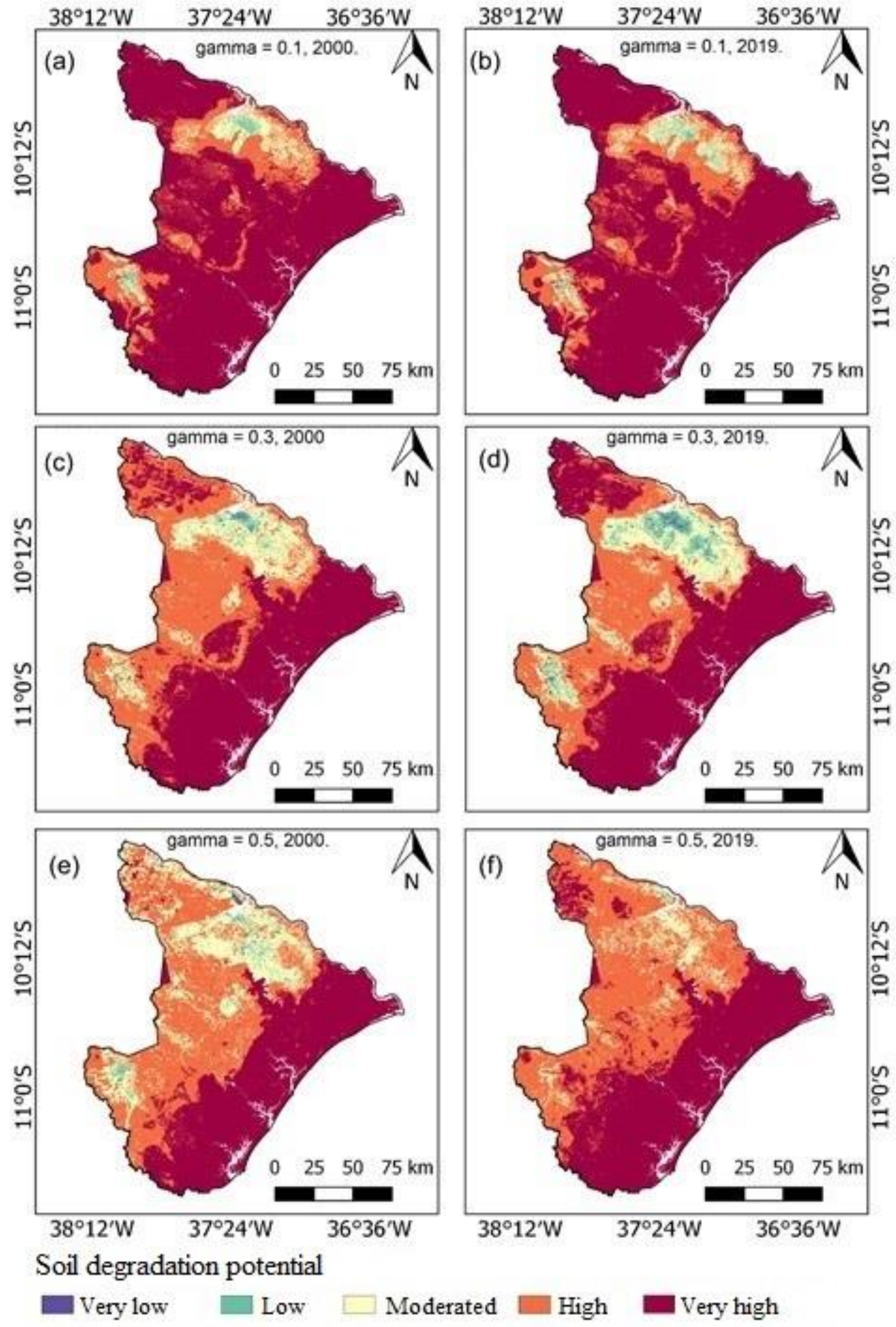


Source: Author, 2021.

Figures 8 and 9 show the results attained through the application of the FGO for each proposed γ value. For the year 2000, the areas with High and Very High PSD decrease as the value of γ increases from 0.1 to 0.5 (Figures 8a, 8c and 8e), but increase from γ = 0.5 to γ = 0.9 (Figures 8e, 9a and 9c). A noteworthy exception is a strip in the northwest, along the border with the state of Alagoas, parallel to the course of the São Francisco River. In this area, there is a steady decrease in the PSD with the increase in the value of γ. A very similar behavior in the PSD is observed for 2019, except for the central-north area, in which the PSD increases as the γ value rises from 0.3 to 0.5 (Figures 8d and 8f, respectively).

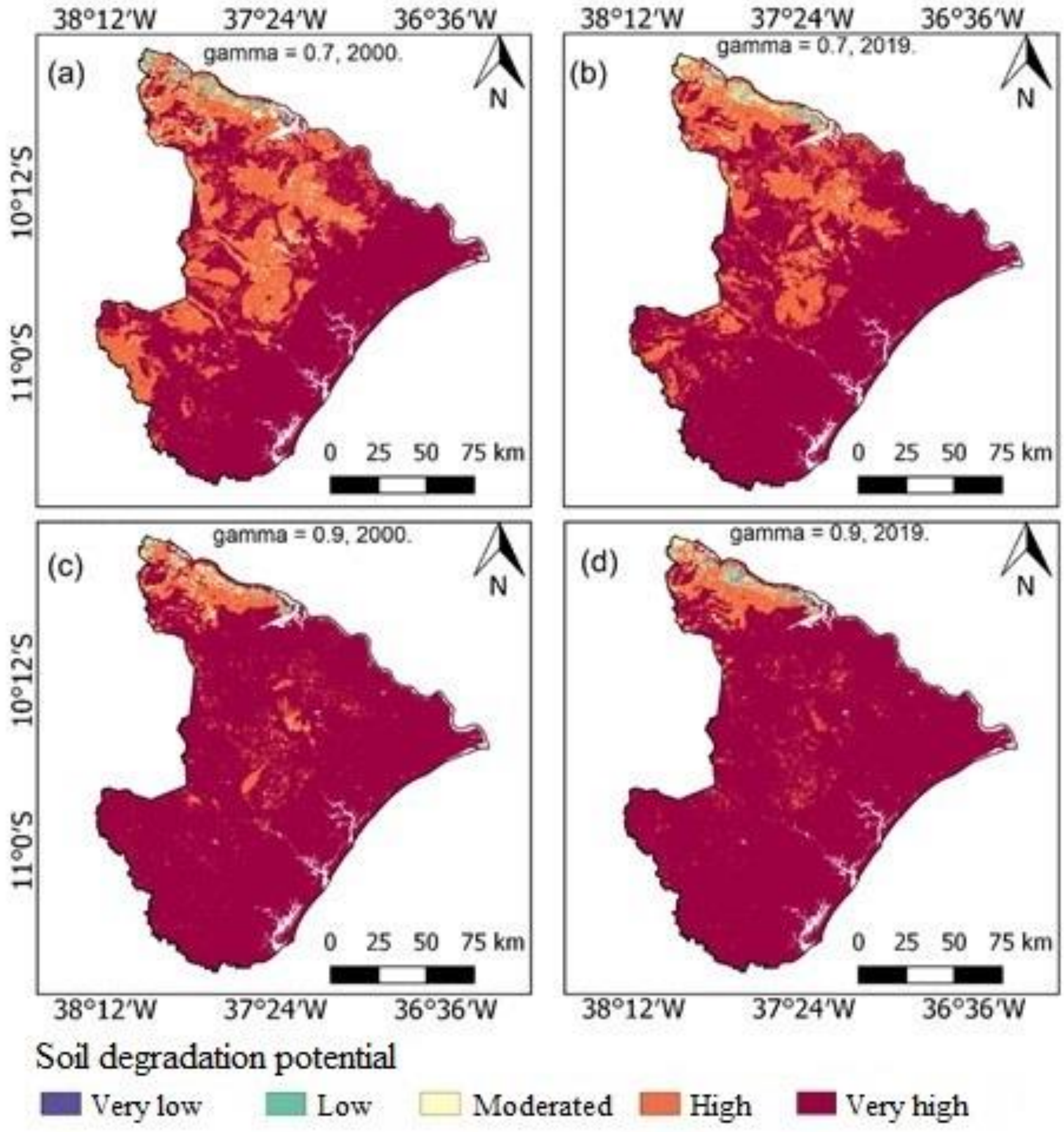
For both years, the High and Very High PSD classes are predominant, although it can be noted that, for γ = 0.3 and 0.5 (Figures 8c through 8f), there are large areas of Moderate and Low PSD areas, especially in the central north and southwest regions. For γ = 0.7 and 0.9 (Figures 9a through 9d), however, the High and Very High PSD classes prevail throughout the state, with the aforementioned exception in the northwest.

Figure 8. Maps for each class of PSD calculated for the gamma values of 0.1 (a-b), 0.3 (c-d) and 0.5 (e-f), for the years 2000 (left) and 2019 (right).



Source: Author, 2021.

Figure 9. Maps for each class of PSD calculated for the gamma values of 0.7 (a-b) and 0.9 (c-d), for the years 2000 (left) and 2019 (right).



Source: Author, 2021.

A visual comparison between the years reveals that there was an overall increase in PSD from 2000 to 2019. Table 4 enables a more precise quantitative analysis on this, by showing the areas that each class of PSD resultant for in each year, in both absolute and percentage values. The areas of Very Low and Low PSD classes decreased substantially, with the first becoming null, and the latter being reduced by almost two thirds, from a value that was already almost negligible (1.7 %). The Moderate class decreased by approximately one third (from 15.14 to 9.37 %), whereas the High and Very High classes underwent considerable expansions, with the first increasing by one seventh (from 38.11 to 43.53).

Table IV. The areas encompassed by each class of PSD in the state of Sergipe in the years 2000 and 2019, for gamma equal to 0.5, in percentage and absolute values (in ha).

	2000	**2019**	**2000**	**2019**
Degradation Potential Class	**Percentage**	**Percentage**	**Area (ha)**	**Area (ha)**
Very low	0,18	0,00	3898,21	0,00
Low	1,70	0,59	36816,54	12777,50
Moderated	15,14	9,37	327889,70	202924,10
High	38,11	43,53	825340,10	942719,90
Very high	44,87	46,51	971740,00	1007257,00

Source: Adapted by the authors.

As for the results from the linear regression, Table 5 displays the Pearson correlation coefficient (r) between the FGO results for γ = 0.5 and the fuzzy values from the input data relative to each variable. However, as stressed by Figueiredo et al. (2014), although causation presupposes correlation, correlation does not necessarily imply causation.

Table V. Table 5. Correlation between the FGO results for γ = 0.5 and the rasters from the input variables.

Variable	***r* (2000)**	**CI**	***r* (2019)**	**IC**
Elevation	0,4790	Weak positive	0,4768	Weak positive
Declivity	0,3018	Weak positive	0,2435	Weak positive
Erodibility	0,1900	Strong positive	0,1432	Weak positive
EVI	-0,2174	Weak negative	-0,2566	Weak negative
Geology	0,7639	Strong positive	0,7382	Weak positive
Geomorphology	0,7104	Strong positive	0,6784	Moderate positive
Pedology	0,6658	Moderate positive	0,4523	Weak positive
Precipitation	0,6675	Moderate positive	0,6052	Moderate positive
Land use of soil	0,2618	Weak positive	0,2988	Weak positive

Source: Adapted by the authors.

Regarding the year 2000, the variables exhibiting the highest r values were geology and geomorphology, with correlations classified as “strong positive”. Pedology and precipitation presented moderate positive correlations, whereas elevation, declivity, erodibility, and land use had correlations within the weak positive range. EVI was the sole variable among the ones researched here to negatively correlate with the PSD, but to a weak extent.

For 2019, geology was the only variable to exhibit strong positive correlation, with geomorphology dropping (relatively to the year 2000) to the moderate positive range. Except for pedology, which dropped from moderate positive to weak positive, all the variables remained within the same ranges of correlations as the ones in the year 2000, and, for all of them, the *r* values decreased in modulus, except for EVI and Land Use, for which the correlation increased by modest amounts.

DISCUSSION

The maps generated from the fuzzy values of each variable (Figures 6 and 7) reveal different spatial patterns of influence on the PSD in the state of Sergipe. For instance, regarding precipitation, the variation in annual accumulated rainfall from coast to interior, is clearly reflected on the pattern of fuzzy values of this variable, which decrease from very high values in the southeast to low and very low in the northwest. This may also be indicative of a causal relationship between precipitation and the intensification of characteristics of other variables that contribute to erosion, such as pedology, geomorphology and vegetation cover. According to Cardoso et al. (2012), the impact of raindrops on the surface constitutes the starting point of erosion by water. In places where erodibility by rain is accentuated, and the surface is not covered by vegetation, high soil degradation can take place, with the consequent losses in soil, water, and nutrients. Lal (2015), affirms that soil physical degradation generally results in a reduction in structural attributes including pore geometry and continuity, thus aggravating a soil's susceptibility to crusting, compaction, reduced water infiltration, increased surface runoff, wind and water erosion, greater soil temperature fluctuations, and an increased propensity for desertification.

Concerning the geological data (Figure 7d), the class of very high PSD is noticed mainly in areas where the geological formation is the one known as Surface Formations (Barreiras Group). The High potential class occurs in the following formations: Estância, Vaza-Barris, Domos Itabaiana e Simão Dias, Marancó and Poço Redondo. Conforming to West (2017), erosion in the Barreiras Group originates from the dynamics of this formation, being dependent on the topographic configuration, since the declivity is related to the speed of change from potential energy to kinetic energy, i.e., to the speed of water masses in the movements responsible for surface runoff. As stated in Shinzato e Dantas. (2017), in the Surface Formations, the predominance of sediments with a low degree of consolidation makes these rocks likely to destabilize and erode in cut slopes if subjected to heavy precipitation events.

With respect to the soil types and how they relate to the resultant spatial pattern of PSD classes, the Acrisols are the ones of greatest extension in the state and the predominant in areas where the very high PSD class is observed (Figure 7f). As for the areas of high PSD class, the most abundant types are the Entisols, followed by the Planosols. Entisols are also present in areas of moderate PSD.

Acrisols exhibit good properties in terms of aggregation and structure, however, they bear obstacles that prevent water infiltration along the soil profile, reducing its permeability and favoring surface runoff, resulting in high erodibility (Neves et al., 2011). Such characteristics of Acrisols in areas where other variables present conditions that favor an intensification of PSD, such as the geomorphology of the Coastal Tablelands – which, as stated in Dantas and Shinzato (2017), is a geomorphological class of tabular topographic forms carved in sedimentary rocks, overall poorly lithified and dissected by a network of channels with low to high drainage densities – coupled with high amounts of precipitation are determinant for the exhibition of very high PSD classes, as seen in Figures 8 and 9. As for the Entisols, Neves et al. (2011) argue that their greatest limitation is the low effective depth, which limits the root development of plants and crops, reducing their support capacity, which becomes more expressive the closer the rock is to the surface. These characteristics give these soil type's little capacity for vegetation sustainability.

As to the land use and cover (Figures 6e and 6f), it is evident that the areas categorized as having a very high PSD are mostly used for pasture, agriculture, and urban infrastructure. It is also seen that pasture areas are spread throughout the state, occurring also in areas of high, moderate, low and very low PSD. For Maiato (2016), conventional agriculture, based on soil mobilization as a way of fighting weeds and preparing the seedbed, is the main cause of soil degradation at global level, but with particularly high incidence in tropical regions.

As far as urbanization is concerned, Brito et al. (2012) assert that the process of urban expansion without an adequate planning and towards inappropriate areas, such as steep slopes and near springs, may result in general environment degradation, affecting the vegetation cover, soil, and water. In Sergipe, the largest cities of the state, including its capital, Aracaju, are located along the coast, where the very high class of PSD was predominant.

CONCLUDING REMARKS

In general, the scenarios obtained from the different values assigned to the gamma exponent indicate a predominance of High and Very High levels of PSD in the state of Sergipe for the two periods studied here (the years 2000 and 2019). These scenarios show that, if the conditions that favor soil degradation are not addressed and controlled, there will be a tendency for areas of high and very high PSD to expand in the state. The following variables are the ones that showed greatest influence in the estimated PSD: geology, geomorphology, pedology and precipitation.

However, proper attention should be paid to variables susceptible to changes in the human timescale, such as precipitation, land use and cover and, consequently, EVI, for which it was possible to observe an increase in the fuzzy values, which rendered them major contributors to the worsening of the PSD in the studied timespan. That is, especially, land use and cover, as it is a variable closely related to human activities. Activities such as agriculture and livestock must adopt sustainable soil management measures. Incidentally, activities that cause suppression of native vegetation, alteration of riverbanks and irregular water courses must be addressed.

Therefore, public management and the society must look out for how the natural resources surrounding them are being explored, especially in areas with accentuated declivity, as well as in soils that are shallow or that are still in the process of formation, such as the Entisols and Acrisols, which are abundantly present in the studied region. Special attention should be given to the Acrisols, as they cover areas primarily used in the region for pasture and conventional agriculture. Therefore, should a disorderly expansion of these activities take place, a future scenario of intensification of the processes of soil degradation in those areas is to be expected.

The model presented in this work must only be used in the context of environmental planning, as it may not reliably represent field reality. Therefore, it is not meant to replace field sampling, but rather to be complementary to it. We recommend efforts towards the improvement of the methodology proposed here, including an *in situ* assessment of sites with high PSD, which will also be useful for the validation of the model based on the collected data. It is also suggested to divide the area under study into sub-areas, according to criteria that are appropriate for the intended scope of each study, e.g., by watershed or administrative territories.

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