University of São Paulo
“Luiz de Queiroz” College of Agriculture

Soil degradation determined by temporal satellite images and environmental variables in São Paulo State, Brazil

Claudia Maria Nascimento

Dissertation presented to obtain the degree of Master in Science. Area: Soil and Plant Nutrition

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Bachelor in Environmental Management

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versão revisada de acordo com a resolução CoPGr 6018 de 2011

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RESUMO

Degradação do solo determinada por imagens de satélite temporais e variáveis ambientais no Estado de São Paulo, Brasil

A saúde do solo é um grande desafio do século XXI. As regiões tropicais são as que apresentam maior expansão em terras agrícolas. Portanto, novas pesquisas sobre o processo de degradação do solo são imprescindíveis para prevenir danos à dinâmica social e ambiental. O objetivo principal deste trabalho foi gerar um Índice de Degradação do Solo em uma região tropical com base nos fatores que o afetam, em uma região tropical com base nos fatores que o afetam A metodologia seguiu os passos de um trabalho já desenvolvido para uma pequena área do interior do Estado. Coletamos imagens da área, obtidas por uma série temporal de imagens de satélite Landsat (1985 a 2019) e determinamos as áreas com solo exposto pela metodologia Geospatial Soil Sensing System. Amostras de solo (0-20 cm) foram coletadas para realizar a espacialização dos atributos do solo por meio do algoritmo de Random Forest. Dados climáticos médios foram obtidos para o período de análise, usando o conjunto de dados CHIRPS para gerar as informações médias históricas sobre os anos de estudo. A temperatura da superfície foi determinada com base nas bandas térmicas Landsat 5 e 8. Usando o modelo de elevação, outros dados de terreno foram obtidos, como fator LS e Slope. Todas essas variáveis foram sobrepostas pelo algoritmo de agrupamento k-means, normalizando-as para uma forma adimensional a fim de gerar um Índice de Degradação do Solo (SDI) (valores de 1, muito baixo a 5, níveis muito altos de degradação). A matéria orgânica (MO) foi utilizada para validar o modelo. Houve uma relação importante entre o SDI e a refletância espectral de superfície exposta do solo, obtida pelo Landsat. Os resultados mostraram que quanto menor a quantidade de OM, maior o nível de degradação. Portanto, o método utilizando dados de sensoriamento remoto multitemporal e variáveis ambientais mostrou-se satisfatório para atender a SDI, que permite a tomada de decisões sobre o uso do solo e políticas públicas.

Palavras-chave: Qualidade do solo, Degradação do solo, Sensoriamento remoto, Imagens temporais de satélite, Landsat, Mapeamento digital do solo

ABSTRACT

Soil degradation determined by temporal satellite images and environmental variables in São Paulo State, Brazil

Soil health is a major challenge in the 21st Century. Tropical regions are the ones with the strongest expansion in agricultural lands. Therefore, novel researches on the soil degradation process are imperative to prevent damages to social and environmental dynamics. The main goal of this research was to generate a Soil Degradation Index based environment co-variables acquired by remote sensing and processed with machine learning. The work was developed in all the complete agricultural area of São Paulo State, Brazil. We used a Landsat time-series (1985 to 2019) and determined the areas with exposed soil using the Geospatial Soil Sensing System methodology. Based on a dataset with soil samples (0-20 cm) we calibrated pixel images and generated thematic maps of clay, and cation exchangeable capacity, CEC. Organic matter was also determined but used for validation and not a co-variable. The specialization was performed using a random forest algorithm. Other co-variables were determined such as land use. The k-means clustering algorithm was used to overlay all variables including historical data of rainfall and surface temperature as well as terrain attributes in order to generate a Soil Degradation Index (SDI) (values from 1, very low to 5, very high levels of degradation). Finally, the model was validated using OM. There was an important relationship between the SDI and the spectral surface reflectance obtained by Landsat. Locations with less OM presented a higher degradation. Therefore, integrating multitemporal remote sensing data and environmental variables proved to be effective to assist the SDI, which allows for land use decision-making and public policies.

Keywords: Soil quality, Soil degradation, Remote sensing, Time-series satellite images, Landsat, Digital soil mapping, Monitoring

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1. INTRODUCTION

The main farming productions from São Paulo State are sugarcane, cattle and orange orchards. Information about farming data is available at "Instituto de Economia Agrícola" (Institute of Agricultural Economics, http://www.iea.agricultura.sp.gov.br). The State of São Paulo is an important national and international agent in terms of the agricultural sector. According to the data of this institute, this region is the world's largest producer of sugarcane ethanol, responsible for around 47% of Brazilian production. The interior of São Paulo is the world's largest producer of orange juice, accounting for 53.51% of industrially produced juice on the planet. The cattle breeding areas produced R$ 7.8 billion, approximately 10% of all the Brazilian productivity. The egg sector participated with about 23% of Brazilian production, in monetary terms this meant a production of R$ 3.4 billion. Therefore, this is an extremely important region for the study and the analysis of better soil practices.

The alteration of natural ecosystems by agricultural activity is impairing soil physical, chemical, and biological processes (Usharani et al., 2019; Ferreira et al., 2021). The land use planning and management are the key for preventing soil degradation (Orchard et al., 2013). Soil quality can only be achieved by the conservation of proper traits, which involve its biomass, structure, water storage, nutrient cycling, biological activity, and diversity (Lal, 2004). Besides, soils are a fundamental component for food and fiber production, as well as maintaining the quality of the region and the world, as they are the foundation of agriculture and the natural vegetation community (Doran; Zeiss, 2000; Nortcliff, 2002).

Conceptually, Lal (2015) grouped four types of soil degradation: physical, chemical, biological and ecological. The soil physical degradation is recognized to regulate soil porosity, water infiltration and retention, surface runoff, soil compaction, land surface temperature fluctuations, soil organic matter and other modifications in soil structure (Rabot et al., 2018). Likewise, soil chemical degradation is described by the loss of soil fertility, reducing cation exchange capacity (CEC) with the increase of aluminum, soil salinization, acidification, alkalinization and nutrient deficiency in plants (Nieder et al., 2018).The third type is soil biological degradation that can be accessed by soil organic carbon (SOC) contents, especially caused by erosion (Veum et al., 2014). Indeed, some authors demonstrated that the decline in native vegetation reduces the SOC, as intensive land use decreases its quality (Dlamini et al., 2014). The reduction of SOC can compromise soil fertility, water retention and erosion increase. Finally, the cluster of physical, chemical and biological degradation generate the fourth type of soil degradation, that is ecological depletion (Lal, 2015). The ecological degradation can be identified by the disturbance in the ecosystem due to change in elemental cycling, soil and organic matter.

Soil organic matter (SOM) is boosted by the land coverage maintenance and is a crucial soil attribute for minimizing soil degradation (Bayer and Mielniczuk, 1997). High levels of SOM help to reduce the degradation by enhancing soil fertility, structure and water infiltration capacity (Lal, 2015). However, inadequate soil management may increase the rate of SOM decomposition, which is influenced by soil surface temperature, physical and chemical properties (Alexander, 1978) and erosion processes (Sanderman and Berhe, 2017).

According to Chaplot et al. (2005), the establishment of annual crops on former forest lands considerably increases the possibilities of soil loss due to erosion. Some tilling procedures can accelerate soil degradation, with negative impacts on the physical, chemical and biological quality, as well as a decrease in productivity (Mendes et al, 2006). Moraes (2016) concluded that tillage systems foster erosion and compaction while also increasing SOM mineralization and soil degradation. Moreover, the constant exposure of soil due to agricultural activity (bare soil) increases the soil temperature and the SOM decomposition rates while decreasing the water infiltration due to the sealing process (Llanillo et al. 2006).

Water retention and availability, mainly in surface layers, are higher in non-bared soils due to their structure, which also explains the lesser susceptibility to leaching (Dalmago et al. 2009; Carvalho et al. 2000). Furthermore, an increase in SOM leads to an increase in the water retention capacity (Weil and Brady, 2017) Galdino et al. (2016) explained that soil degradation is accelerated by exposure to erosive agents intensifies its degradation, particularly in areas covered by pastures on Leptosols, which have a high susceptibility to soil loss and sediment transport. The lack of vegetation, especially in more mountainous or sloping areas, can also accelerate the degradation process (Eroğlu et al., 2010). Monteiro et al. (2018), show that areas with high to very high degradation, had soils with a longer exposure duration.

The soil topography, which is represented by the steepness and landscape shape, influences the surface runoff rates, as a key factor along with climate, driving the soil loss (Fernandes et al., 2014). The infiltration rates in steep terrain are lower, encouraging surface runoff and enhancing drainage channel formation (Mello et al., 2021) This scenario stimulates soil erosion across the landscape and necessitating adequate management (Weill e Sparovek, 2008) and a reduction in SOM (Starr et al., 2000).

The soil degradation process mentioned can also be affected by the soil texture. Indeed, lands with higher aggregate stability, such as clayey soils, are less predisposed to degradation due to its lower erodibility rate, which is a measure of the susceptibility to detachment and transport of ground particles by rainfall and runoff (Elwell, 1986).

Current advances in geographic information system (GIS) and remote sensing (RS) technologies are fostering the monitoring and management of large territories (Barvels and Fensholt 2021; Hu et al., 2021; Vieira et al., 2021). RS is characterized by the use of sensors to process any geographical information and are positioned on platforms such as airplanes or spacecrafts for data transmission to support the study of events occurring on the Earth's surface (Novo, 2010). Therefore, RS tools can be employed as proxies to extract and describe the environmental process of soil degradation as well as its relationship with anthropic activities (Cunha et al., 2012). Several projects attempted to build land degradation models using innovative technology. For example, Chaves et al. (2015) employed RS to collect information about the vegetation, soil, and topography in order to develop a model to estimate soil degradation. Barbosa et al. (2007) correlated the dynamics in land use with the soil degradation through digital processing and temporal analysis of a Landsat 5 image. Mota et al. (2011) prepared a map of soil degradation vulnerability through GIS and multicriteria additive methodology, taking into account the geology, geomorphology, pedology, vegetation, and climate information.

A widely used technique to measure soil degradation is the Revised Universal Soil Loss Equation (RUSLE). This method employs the equation that depends on the variables such as topography, cover management, support practice, erodibility and soil loss tolerance (Renard 1997; Lu et al., 2004; Santos et al., 2015). Another method for assessing soil degradation, for example, considered the following factors: soil erosion by water, bioclimate indicator, and topsoil depth (Diodato and Ceccarelli, 2004). Besides, new approaches that use spectral to express land degradation are being developed (Chikhaoui et al., 2005; Chabrillat, 2006). for example, Dantas et al. (2018) used a method that considers land use, NDVI, precipitation, livestock, and erodibility in the evaluation of degradation. However, there are few works that attempt to reach fine resolution (30 m) in great areas in South America, where pressure for lands and agriculture has become the focus of the world's needs. This takes us to the necessity to achieve faster techniques to sow the 'big picture' of the situation and thus take actions. Despite this, most papers as indicated use land use, soil properties and other co-varieties but there is absence on the exposed soils. Soil exposed such as carbon degradation, microorganisms alteration, erosion, water loss, among others.

Said this, the aim of this work is to introduce a new co-variable to the degradation index: the bare soil factor. The main objective was to develop a soil degradation index for the entire State of Sao Paulo Brazil where we have one of the most important agriculture systems. Each chosen variable was expected to contribute to the determination of soil degradation susceptibility. We expect an important relationship between soil properties and degradation. Also, we expect that areas with more agriculture present greater degradation.

2. MATERIALS AND METHODS

2.1. Study area

The São Paulo State is located in the Southeast region of Brazil and covers a total of 248,209 km^2. The Cfa is the predominant climate, which occupies 33.4% of the territory, presenting characteristics such as hot summers and an undefined dry season. The other types of climate present in the study area, in descending order, are Aw, Cwa, Cfb, Cwb, Af and Am (Alvares et al., 2013). The annual precipitation of São Paulo State varies from very high quotas, as observed on the slopes of Serra do Mar, which can reach 4500 mm, to moderate indices, as in stretches of the Depressão Periférica, between 1000 and 1100 mm (Nery et al., 2004).

The predominant soil classes in the area are Ferralsol, covering 38.14%, followed by Lixisol, with 37.63% (Rossi, 2017). The flowchart of the steps performed in this work can be seen in Fig.1

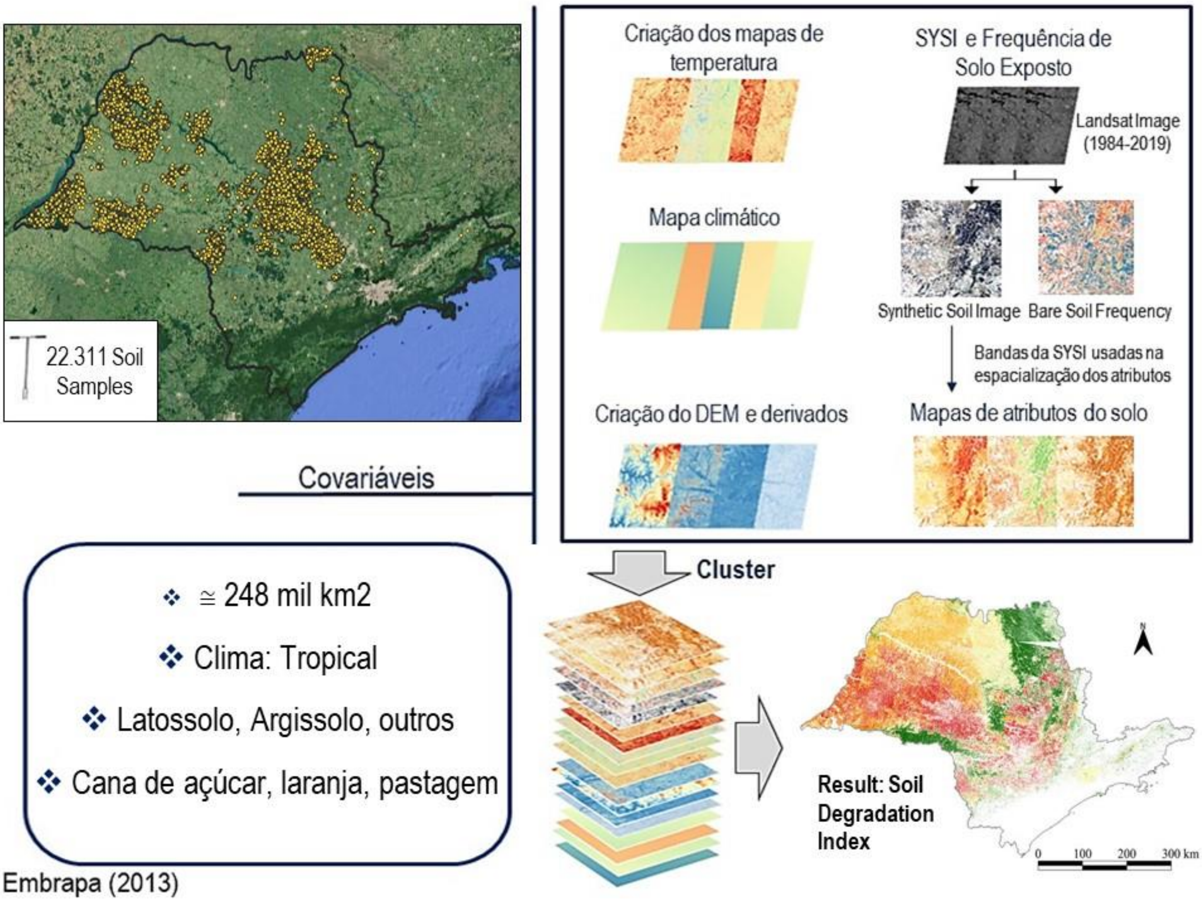

Figure 1. Flowchart of the methodology performed.

2.2. Obtaining the environmental variables used in the calculation of soil degradation index

In total, 11 environmental variables were used to construct the soil degradation index map. The following sections describe how each variable was obtained.

2.2.1 Synthetic soil image (SySI) and bare soil frequency (SF)

Demattê et al. (2018) developed a procedure for obtaining a single synthetic image, which would represent bare soils by combining multi-temporal satellite image information. The method called Geospatial Soil Sensing System (GEOS3) uses a Landsat database to generate a Synthetic Soil Image (SYSI) with six spectral bands, nm: blue (450–520), green (520–600), red (630–690), NIR (760–900), SWIR1 (1550–1750) and SWIR2 (2080–2350), which present a multitemporal composition of pixels with bare soil from 1984 to 2019.

The SYSI was generated through the Landsat images database from 1984 to 2019 through the Google Earth Engine platform. Following the GEOS3 methodology, indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio 2 (NBR2) and others described by the authors, were used to identify and remove these features and to capture only the pixels that showed bared soil. Subsequently, the generated images were overlaid and the median spectral reflectance was selected. The composite of all TESS values generates a unique image as a SYSI. The GEOS3 method also provides the frequency of times that the soil was exposed. This information is very relevant for the degradation research, which can improve the understanding of the relationship between remote sensing indicators and soil properties.

2.2.2 Soil attributes data and spatial prediction

The legacy soil observations gathered across the São Paulo State came from the previous surveys developed by the Geotechnologies in Soil Science Group (https://esalqgeocis.wixsite.com/geocis) and others (Nanni et al., 2004; Terra et al., 2015; Rizzo et al., 2016; Fongaro et al., 2018; Gallo et al., 2018; Demattê et al., 2019; Mendes et al., 2019). Surface (0.00-0.20 m) samples (n = 22,311) were collected with augers in georeferenced locations, mostly following the sampling strategy of toposequences or grid schemes.

The chemical and physical analysis were determined according to Camargo et al. (2009). The soil attributes selected for mapping purposes were Clay (g kg^{-1}), Cations Exchange Capacity (CEC, mmol kg^{-1}) and Organic Matter (OM, g kg^{-1}).

The soil attributes were spatialized using the same methodology as Safanelli et al (2021). The Random Forest algorithm was applied in this study. The Random Forests algorithm is a set of many regression trees built with bootstrap samples and randomized predictors. To define the optimal hyperparameters for each soil attribute a grid search was performed. The number of trees in the forest, the number of random predictors tested at splits of each tree, and also the minimum number of samples at the tree leaves were tested, to choose those that resulted in smaller prediction errors. To optimize the number of trees of the forest, the following values were tested: 30, 60, 100, 200 and 500 trees.

In total, 13 predictors were available to predict the attributes, SYSI blue, SYSI green, SYSI red, SYSI NIR, SYSI SWIR1, SYSI SWIR2 and seven terrain attributes derivatives of the Digital Elevation Model (DEM) built using the Shuttle Radar Topography Mission (SRTM) image: elevation, slope, northness, eastness, horizontal curvature, vertical curvature, and terrain shape index. More details on terrain attributes are found in Safanelli et al. (2020). The values of 3, 5, 8, 11 and 13 predictors were investigated for defining the number of random predictors. Further, the values of 10, 20, 30, 40, 50, 100, 200 and 500 observations were tested for minimum number of samples at the tree leaves.

The sample data were randomly divided into two sets, the training set and the model test set. The training set was determined by collecting bootstrapped samples of each regression tree, whereas the testing set was defined by the remaining samples (out of the bag) that were not selected at each bootstrapping. Bootstrapping is a method that samples observations with replacement to the same size of the dataset, covering, in general, around 67 % of the entire dataset. We applied the bootstrapping method up to 500 times, which is equivalent to the maximum number of trees tested for the random forest.

2.2.3 Land data

2.2.3.1 Terrain attributes

The Digital Elevation Model (DEM) was generated using the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007) with 30 meters resolution. The result was processed in QGIS 3.10 software in order to achieve its attributes, using the Basic Terrain Analysis tool in the SAGA GIS 2.1.3. software (Conrad et al., 2015). The co-variables produced by this methodology were the LS Factor, and Slope. The LS factor was calculated based on the methodology proposed by Desmet and Govers, 1996. These are the parameters that will be used to analyze degradation levels.

2.2.3.2 Land surface temperature (LST)

Images from Landsat 5 and 8 were obtained from the "Earth Explorer" platform from the USGS (United States Geological Service). The images were acquired from Landsat 5 TM sensor with resolution of 30 meters for the visible (VIR), near infrared (NIR) and short wave (SWIR) and 120 meters for the thermal infrared (TIR). Landsat 8 has the Operational Land Imager sensor (OLI) with 9 spectral bands while the Thermal Infrared Sensor (TIRS) includes 2 infrared spectral bands with the spatial resolution of 100 m (USGS, 2017). To process the data, images were needed to cover the entire study area in September and October (dry season and low cloudiness) of the years 1985 to 2019. The criterion used for choosing these months of the year was the greater consistency in finding cloudless images.

For the years 1984 to 2014, the Landsat 5 (sensor TM) images were used and for 2014 to 2019, the Landsat 8 (OLI and TIRS sensors). The thermal images of Landsat 8 presents some problems due to the dispersion of the stray light that reaches the sensor, which leads to inaccurate results. Several algorithms were tested by USGS and a correction was applied to the images from February 2014. The adjustment still remains with a significant amount of variation, especially within Band 11 (Pires; Junior, 2015) and USGS do not recommend using this band data in science studies (NASA, 2014). Therefore, band 10 was utilized to compute the LST from 2014 to 2019.

The LST was estimated using the “Land Surface Temperature” plugin (Ndossi; Avdan, 2016) in QGIS software 2.18 version. At first, the digital numbers of the thermal bands (band 6 for Landsat 5 and band 10 for Landsat 8), (DN) were converted into spectral radiance. Then it was converted into brightness temperature which represents the temperature of a black body under the assumption of uniform emissivity (Sayão et al., 2018). The NDVI number was calculated using visible and near-infrared bands (bands 3 and 4 for Landsat 5 and bands 4 and 5 for Landsat 8, respectively). The next step was to calculate the Land Surface Emissivity (LSE) proposed by Zhang et al. (2006) through the NDVI algorithm. Using the LSE, the LST was estimated with the inversion of Plank’s equation, methodology that does not depend on atmospheric parameters that could generate some error. (Ndossi; Avdan, 2016). The mean of historical LST from 1985 to 2019 was calculated through the Raster Calculator tool in QGIS software. In the Raster Calculator tool LST in Kelvin degrees was subtracted 273.15 to convert to Celsius.

2.2.4 Climatic data

The CHIRPS Daily (Climate Hazards Group InfraRed Precipitation with Station Data, version 2.0 final) dataset was used to calculate mean annual precipitation from 1985 to 2020 at a resolution of 4.8 km (Funk et al. 2015). All of these maps were created using Google Earth Engine (GEE) and upscaled to 30 m pixel size using ArcGIS10.3's Spline interpolation. Then, the historical mean was generated using the Raster Calculator tool in QGIS software.

2.2.5 Land use/ Land cover

Land-use/land-cover (LULC) changes and their management during the time can have significant effect on soil degradation and surface runoff (Gebresamuel et al. 2010). Therefore, it is very important to evaluate LULC history in the study of soil degradation. For Briassoulis (2020) the term "land use change" means quantitative or qualitative changes in the area. Together, Vezzani and Mielniczuk (2009) explain that such processes as deforestation, large agricultural plantations and agricultural management of soils, that is, processes of land use change, alter the quality of the soil, compromising the sustainability of the productivity of environmental quality. , despite the contribution to productivity.

LULC history maps were reclassified for every three years from 1985 to 2019 based on the methodology explained in Tayebi et al. (2021). For this purpose, LULC maps were obtained from MapBiomas Collection 5 data that show the annual LULC maps on a 30 m resolution (https://mapbiomas.org/) (Souza et al. 2020). The legend of the Mapbiomas LULC maps were simplified from 30 to just 5 major classes (agriculture, forest, pasture, water, and urban), in order to make it easier to visualize and understand the changes that have occurred. Then, the frequency of land use changes for every three years from 1985 to 2019 were computed for each LULC class and in each pixel according Equation (1) in ArcGIS10.3 (Tayebi et al. 2021):

$$FLCi = (ai/n) \times 100 \qquad (1)$$

where $FLCi$ is the temporal frequency of a specific LULC class for each three years; ai is the count of a specific LULC class that occurred over time and n is equal to 3 (the total number of LULC maps).

The LULC modifications can be seen in the value of $PLCi$. Therefore, If $PLCi$ has the greatest values (near to 100), the LULC class did not change over those three years, and if $PLCi$ has the lowest frequency (zero), the LULC class did not exist throughout those three years

(Tayebi et al. 2021). Finally, from 1985 to 2019, a LULC history map was created based on the frequency of all LULC classes for each of the three years.

2.3 Generating and validating the Soil Degradation Index

The Soil Degradation Index (SDI) was created in R software with the "cluster" package, through the method of k-means, by clustering the variables: CEC, Clay and OM; LST, Rainfall; DEM, LS Factor, Slope; SYSI and the bare soil frequency (SF). It was used five categories of degradation as also detected in a smaller area (Nascimento et al., 2021). Then, the SDI was reclassified into five categories to develop a standard degradation ranking, which goes from 1 to 5. The method used Clay and CEC values to delimit the levels, both for the better grouping of the data, which did not overlap values among the different indexes and for their importance in soil quality. In order to understand the internal soil deterioration in the land, the soil physical and chemical attributes are needed, for these are relevant attributes for soil structure preservation, decreasing erosion rates and improving its fertility, providing a healthy soil (Newman, 1984; Brady and Weil, 2013). So, the higher the CEC and Clay group values composed by the R software, the lower the SDI value.

For validating the SDI, we used the spatialized Organic Matter map. This soil attribute was used as a qualifier since this variable is fundamental in terms of soil quality, permeating a series of attributions, such as plant nutrition, participation in soil chemistry, physics and biology, maintenance of environmental processes such as gas emissions and effective participation in the sustainability discussion of agriculture. The procedure was performed in R software.

3 RESULTS AND DISCUSSION

3.1 Synthetic soil image (SySI) and bare soil frequency (SF)

The use of the Google Earth Engine tool for the generation of SYSI (Fig. 2a) and the bare soil frequency (Fig. 2b) proved to be a very agile platform that allowed the images to be generated in a much shorter period of time.

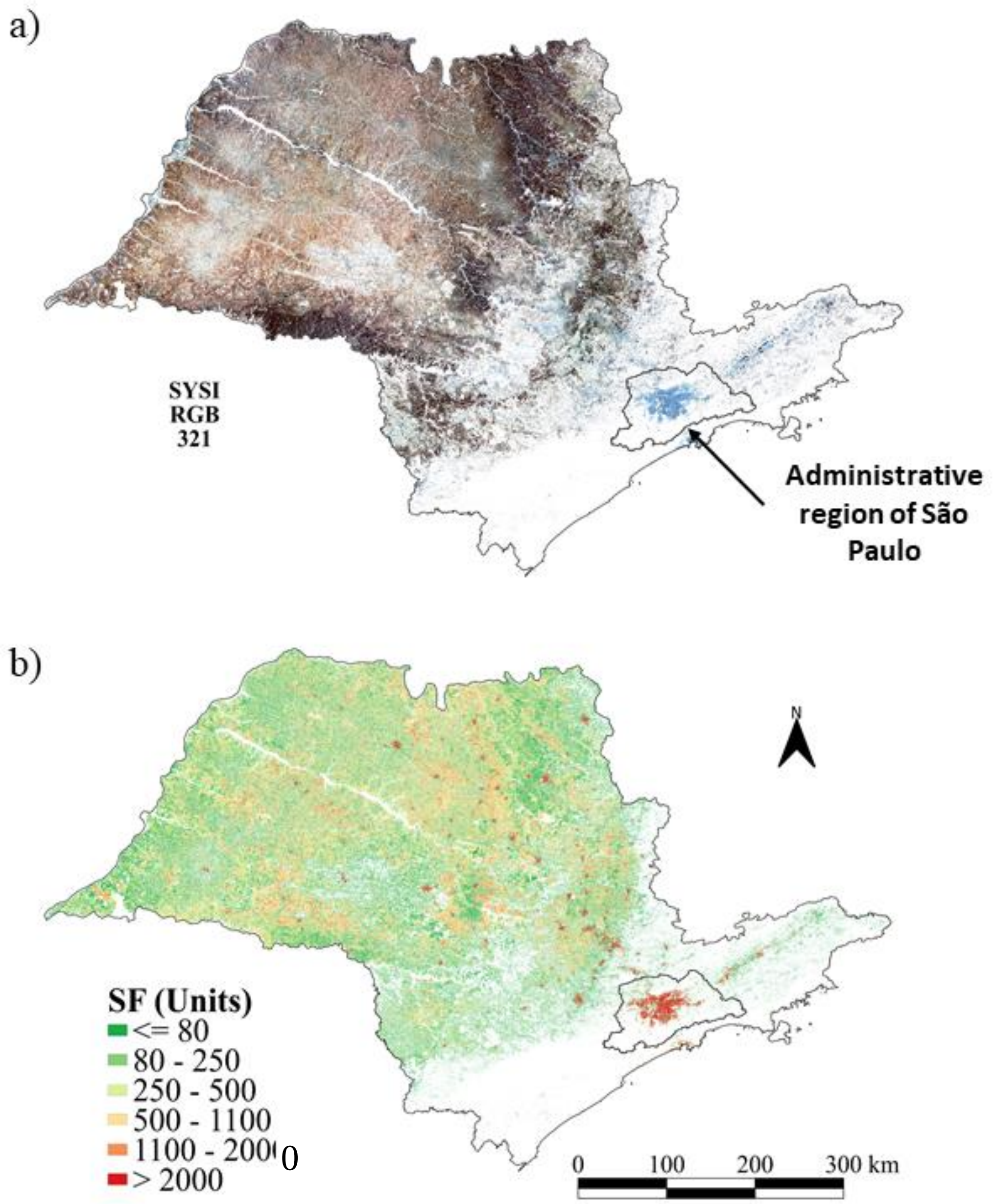

Figure 2. São Paulo State maps of a) Synthetic soil image (SYSI); b) bare soil frequency (SF)

In fig. 2, an administrative area of the State was highlighted, where the São Paulo municipality and several other municipalities in its adjacency are located. To visualize the spectral image of the bare soil (Fig 2a), the natural color composition (RGB - 321) was used. We can verify the frequency of times that the soil was bared (fig. 2b) in this region. The pixels in this image were represented in a range of colors from green (lower exposure) to red (greater exposure). In the first case, these areas are covered by forest, which did not showed land use changes throughout the years. Agriculture areas presented high frequency of bare soil due to land tillage, differently from pasture.

The temporal image with exposed soil information is a very important variable in the generation of the index, since it can indicate areas that are easily degradable or already degraded. Fongaro et al. (2018) agrees that a temporal image of exposed soil is important for generating a continuous and general view of the soil situation.

3.2 Soil attributes data and spatial prediction

The physical (Clay - Fig. 3a), chemical (CEC - Fig. 3b) and biological (OM - Fig. 3c) spatialized soil attributes influence several important processes in soil dynamics. A soil with a lower amount of these attributes leads to few aggregates and weak structure. Then, the soil becomes very susceptible to erosion (Andreoli et al., 2014). Therefore, those are valuable attributes in the determination of soil degradation. Among the five ranges of values observed, those with the highest amount of Clay and CEC were those classified with the lowest degradation index. The Organic Matter was not contabilized since this variable was used for validation.

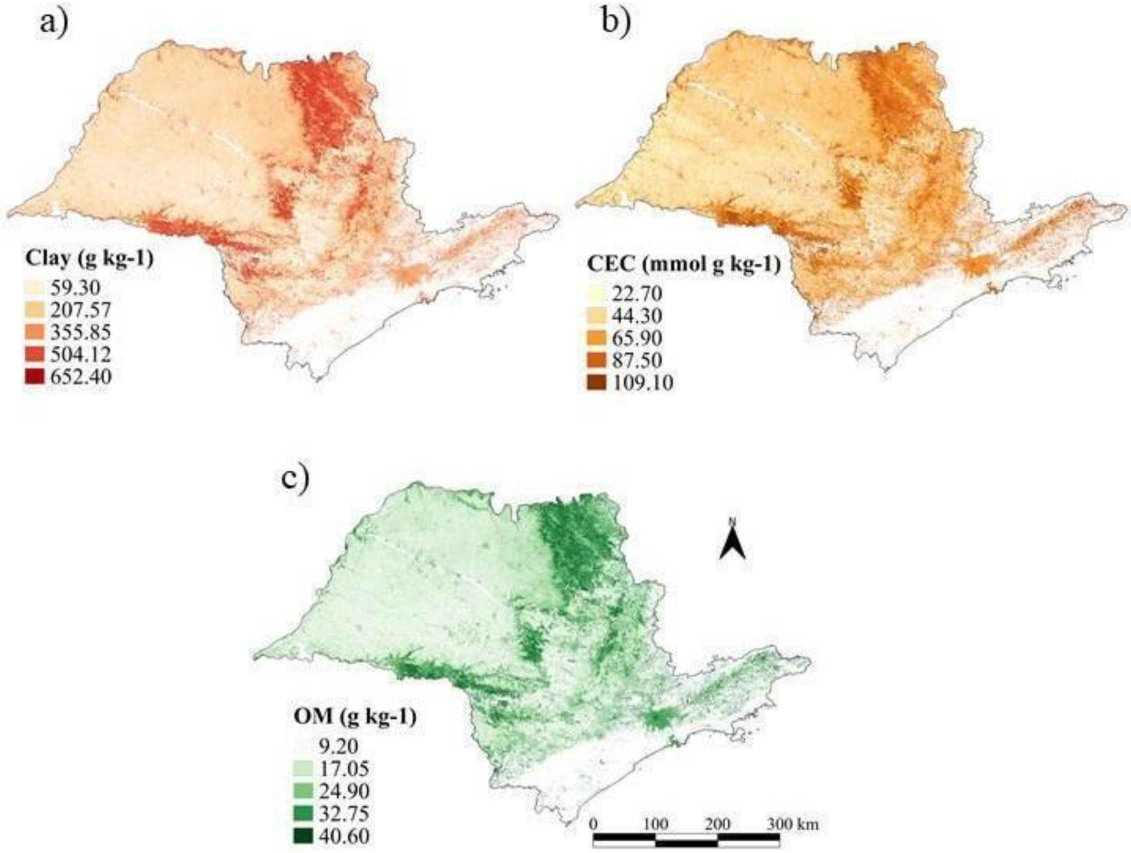

Figure 3. São Paulo State maps of a) Clay; b) CEC and c) OM.

The statistical parameters of the best models used to predict soil attribute maps are shown in Table 1.

Table 1. Performance evaluation of soil attributes prediction

Attribute	RMSE	RPIQ	R^2
Clay (g kg^{-1})	8.56	1.67	0.69
OM (g kg^{-1})	6.10	1.42	0.41
CEC (mmol kg^{-1})	32.62	0.82	0.19

RMSE: root mean squared error. RPIQ: ratio of performance to the interquartile range. R^2: coefficient of determination. OM: Organic Matter. CEC: Cations Exchange Capacity.

The clay map presented the best predictive performance (R^2=0.69, RMSE=8.56 and RPIQ=1.67), followed by the OM (R^2=0.41, RMSE=6.10 and RPIQ=1.42) and then the CEC (R^2=0.19, RMSE=32.62 and RPIQ=0.82).

The low value of CEC validation may show that it is noisy data and high variability, but it has a significant trend. The different level of attribute variability affects the accuracy of these predictions. Still, low R^2 values can indicate a real relationship between the predictors and the response variable.

3.3 Land data

3.3.1 Terrain attributes

The relief and its slope dictate the water flow and speed, carrying soil particles from the summit to the slope end. Therefore, this is an important variable for land degradation modeling. The DEM and its variables can be seen in Fig. 4a-c.

The elevation map (Fig. 4a) presents values that can reach above 1000 meters. The territory of the State has the lowest relief values in the coastal strip. Then, from the southern part of São Paulo to the northeast region, there are the highest relief values. To the west of the State The surface of the territory presents altitudes that can vary from 300 to 900 meters

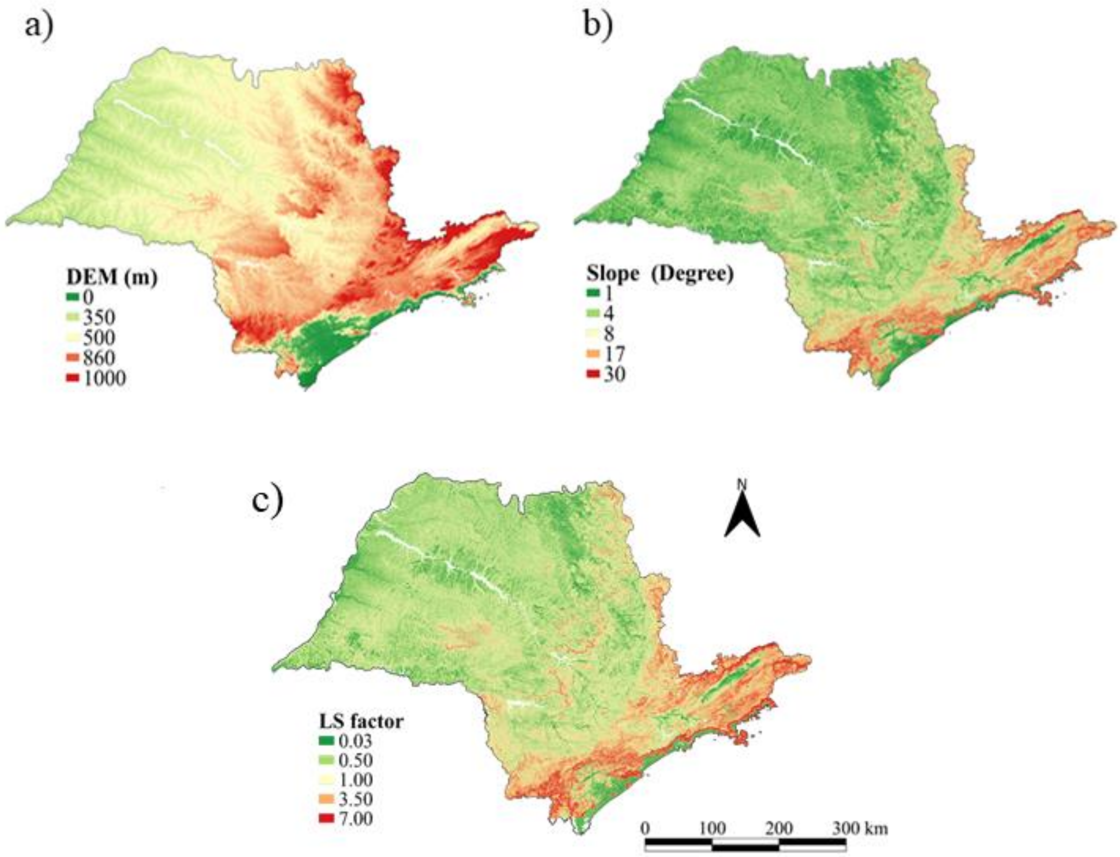

Figure 4. São Paulo State map of the terrain attributes: a) digital elevation model; b) slope; c) LS factor

The processing of these terrain attributes enables the quantification and spatial representation of areas with different limitations to use, which may contribute to the observation of environmental susceptibility (Maganhotto et al., 2013).

The slope (Fig. 4b) values in the study region vary from 1 to 30. According to Lepch et al., (1983), areas with a slope above 15% can provide a greater risk for erosive processes, and should be more restrictive in terms of their use. According to these authors, from 15% onwards, there is also a continuous decrease in aptitude.

The LS Factor (Fig. 4c) is an essential parameter to quantify the erosion generated due to the influence on surface runoff speed, depending on the slope steepness factor (S) and slope length factor (L) (Beskow et al., 2009), that means, the LS Factor increment is related to the water runoff and soil erosion. The state of São Paulo has values from zero to about seven for the LSfactor parameter. According to Mansor et al. (2002), potentially critical areas present values from 6 to 10 and values from 4 to 6 can trigger erosive processes depending on the soil tillage.

3.3.2. Land Surface Temperature

The highest values of LST were obtained in the northern region of the state and the lowest in the south (Fig. 5a). The western region of the state showed intermediate to high degree values. The LST is an important factor for the development of plants, since it controls the soil evaporation, aeration and biochemical processes (Allen et al., 2011). Also, LST can provide information on the physical properties of the surface, climatic conditions and human activities that affect the environment (Mao et al., 2012). In addition, higher soil temperatures increase microbial activity and hence the decomposition of SOM (Weil and Brady, 2017; Yan et al., 2017).

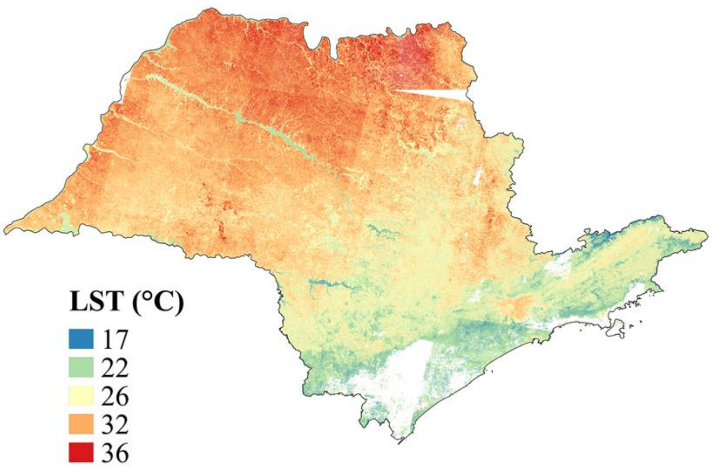

Figure 5. São Paulo State historic mean of the a) LST

3.4 Climatic data

The highest values of annual precipitation are found in the south and east of the state, mainly in the coastal zone. The lowest values are found in the north and west of the state (Fig. 6). Medeiros et al. (2016) found a similar distribution in the state for rainfall erosivity. Along with the high average annual temperatures, the irregular distribution of the rainfall may contribute to the desertification process (Silva, 2015) and its intensity, frequency and duration can lead to erosion process (Santos et al., 2010). Precipitation intensity can be a factor of soil loss. That is because of the energy that the drops reach the ground and the runoff are able to detach and carry the sediments, especially in uncovered soil with low aggregation (Carvalho et al., 2009).

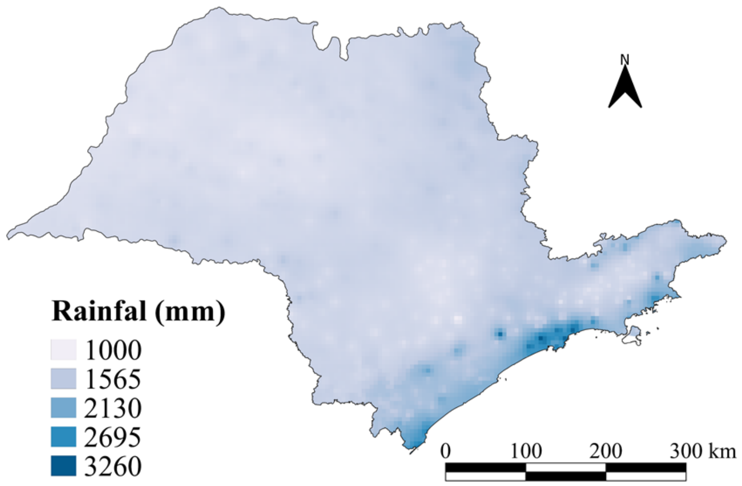

Figure 6. São Paulo State historic mean of the rainfall information.

Castellano and Nunes (2012) suggest that there is the possibility of anthropic factors having effects on these two climatic variables analyzed, even in a short period of time. However, important parameters for understanding climatic effects in the soil degradation process should be evaluated, such as the type of pollutants and the time of permanence in the atmosphere and the direction and speed of the winds.

Mello et al. (2008) reported that geoprocessing is one of the main branches of climatology studies, being important in the use of techniques for better interpolation of spatial rainfall data. In the same way, Marcuzzo (2016) found the importance of this technology in his study. Reis et al. (2005) understand that the use of geographic information system (SIG) facilitates the verification of the way these precipitations are distributed in space and Hashmi et al. (1995) agree that this technology allows to cover large regions with agility and precision.

3.5 Land use/ Land cover

The generated LULC map can be seen in Fig. 7. The average land use and land cover map for the years 1985 to 2019 was acquired. Of the total territory, about 41% is occupied by grasslands, 28% agriculture and 21% by forests.

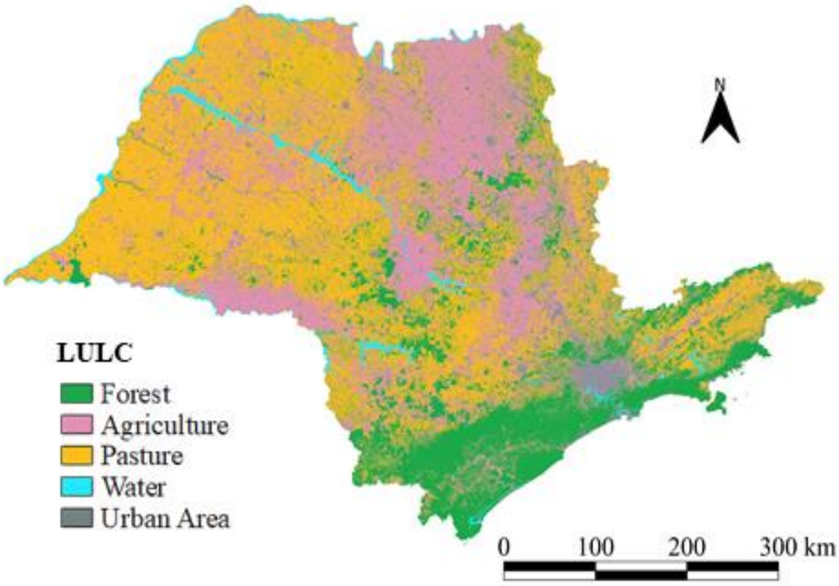

Figure 7. São Paulo State map of the land use/ land cover (LULC) mean from 1985-2019.

In the state of SP, there was a recognized expansion of annual crops over the years, such as sugar cane, which must be associated with government incentives given around the 1970s, for the production of ethanol. However, as indicated by Ferreira et al. (2015), this occupation occurred mainly in pasture lands. The Calaboni et al. (2018) research observed that over the study period there was a general decrease in pasture areas from 1996 onwards, which type of use became more expressive in the west of the state, while annual crops expanded throughout the entire territory. Moreover, despite the forest cover being low in the municipalities, there was an increase in forest regeneration.

3.6 Soil degradation index

Clustering the chosen variables generated five categories of the risk of land degradation, leveled as (1) very low, (2) low, (3) medium, (4) high and (5) very high (Fig. 8).

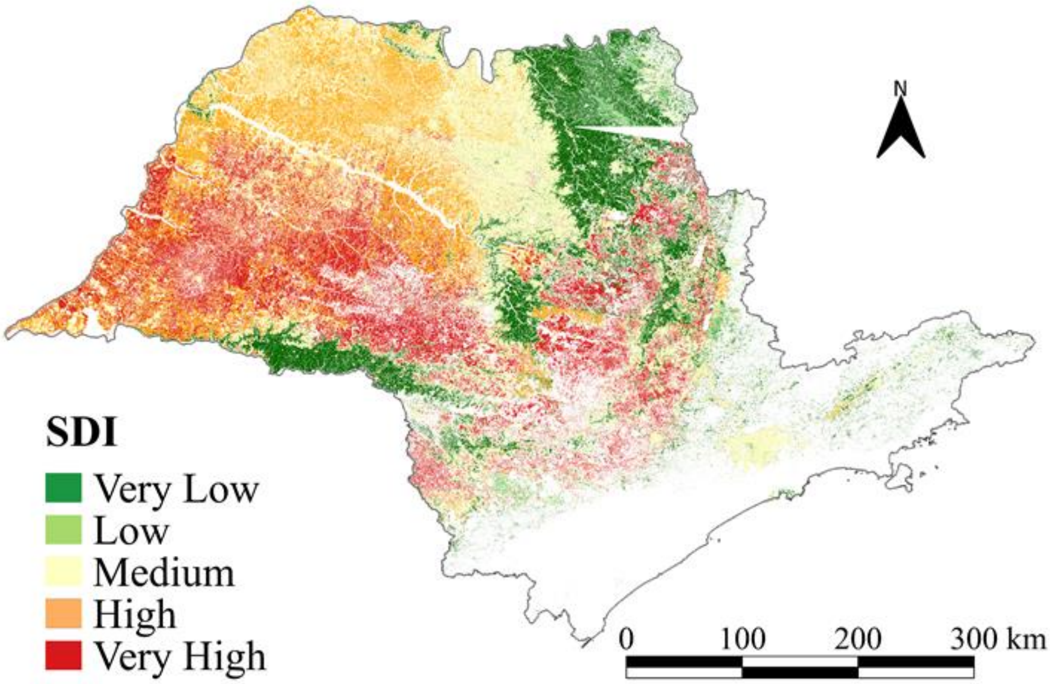

Figure 8. Map of the Soil Degradation Index (SDI) of São Paulo State

The level classification followed the Nascimento et al. (2021) method. The CEC and clay attributes were used in order to sort each group, as seen in Table 2. Therefore, we attributed to clay the following intervals and their respective classes of susceptibility to degradation: <12% clay – Very high risk of degradation; 12-18% - high; 18-30% - medium; 30-40% - low; >40% - very low.

Table 2. Generated statistics of the variables used to create the different levels of SDI

VERY LOW															
	DEM	LS_Factor	CTC	Clay	Slope	Rainfall	LST	LULC	SYSI_1	SYSI_2	SYSI_3	SYSI_4	SYSI_5	SYSI_7	SF
Min.	281,32	0,03	32,11	66,76	1,42	1222	2939	2	7	-282	102	224	784	744	7
1st Qu.	583,11	0,25	77,46	368,74	370,21	1380	3012	4	394	602	877	1257	1648	1498	63
Median	642,16	0,33	85,68	447,51	586,32	1416	3024	4	442	664	965	1388	1848	1665	171
Mean	649,74	0,37	85,36	434,29	646,41	1420	3024	4	449	669	961	1390	1873	1688	260
3rd Qu.	709,42	0,43	95,01	512,43	852,47	1450	3036	5	494	729	1051	1524	2072	1853	377
Max.	1094,95	5,01	108,93	645,77	3785,84	1858	3155	26	1295	1579	2317	2664	4186	3690	3601

LOW															
	DEM	LS_Factor	CTC	Clay	Slope	Rainfall	LST	LULC	SYSI_1	SYSI_2	SYSI_3	SYSI_4	SYSI_5	SYSI_7	SF
Min.	252,86	0,03	30,39	70,26	1,14	1264	2955	3	47	-36	236	409	914	858	6
1st Qu.	512,00	0,24	62,14	252,23	244,00	1543	3025	8	480	728	1021	1480	1947	1750	164
Median	603,86	0,33	70,17	309,09	374,43	1613	3036	9	534	803	1120	1628	2181	1943	564
Mean	590,11	0,37	72,43	326,32	422,11	1603	3036	9	542	808	1122	1623	2177	1943	766
3rd Qu.	648,14	0,43	82,19	397,13	545,00	1649	3047	9	591	880	1222	1772	2403	2129	1215
Max.	1165,86	5,21	108,36	621,86	3102,14	2180	3193	25	1708	2061	3130	3496	4478	4072	6444

MEDIUM															
	DEM	LS_Factor	CTC	Clay	Slope	Rainfall	LST	LULC	SYSI_1	SYSI_2	SYSI_3	SYSI_4	SYSI_5	SYSI_7	SF
Min.	259,97	0,03	27,22	62,06	1,25	1199	2946	4	75	111	433	657	1132	1069	64
1st Qu.	505,42	0,24	51,59	170,06	218,53	1353	3022	12	570	888	1247	1847	2453	2183	251
Median	545,39	0,32	57,89	215,66	357,90	1395	3032	13	625	965	1354	2004	2686	2381	681
Mean	552,39	0,37	58,96	228,34	394,39	1391	3031	13	643	985	1371	2016	2702	2399	1022
3rd Qu.	587,89	0,43	64,94	268,80	526,33	1428	3041	13	693	1058	1475	2172	2933	2594	1555
Max.	951,92	5,14	108,70	626,55	3047,81	1784	3154	49	2143	2859	3474	4240	5698	5171	7250

HIGH															
	DEM	LS_Factor	CTC	Clay	Slope	Rainfall	LST	LULC	SYSI_1	SYSI_2	SYSI_3	SYSI_4	SYSI_5	SYSI_7	SF
Min.	267,69	0,03	25,26	60,54	1,00	1182	2960	1	117	383	798	1123	1662	1561	6
1st Qu.	412,69	0,24	37,82	112,64	230,56	1319	3028	2	595	963	1430	2138	2949	2638	124
Median	444,63	0,33	42,91	137,97	339,44	1355	3037	3	649	1034	1522	2276	3157	2820	258
Mean	460,20	0,37	44,94	148,13	370,15	1357	3037	3	662	1048	1535	2294	3174	2838	352
3rd Qu.	484,31	0,43	49,78	171,14	473,50	1388	3046	4	712	1116	1626	2434	3381	3018	477
Max.	805,00	4,90	108,57	581,31	2751,56	1670	3154	24	2076	3165	3964	4882	6259	5695	6601

VERY HIGH															
	DEM	LS_Factor	CTC	Clay	Slope	Rainfall	LST	LULC	SYSI_1	SYSI_2	SYSI_3	SYSI_4	SYSI_5	SYSI_7	SF
Min.	278,92	0,03	25,25	60,40	1,00	1174	2952	1	115	291	964	1372	1754	1644	6
1st Qu.	454,50	0,25	35,55	86,88	305,67	1302	3018	2	652	1066	1577	2389	3397	3022	92
Median	492,83	0,33	39,87	100,03	444,25	1327	3028	2	711	1144	1675	2534	3625	3227	198
Mean	497,53	0,37	41,33	108,98	465,80	1328	3027	2	729	1169	1700	2571	3654	3255	279
3rd Qu.	535,83	0,42	45,02	126,68	598,25	1357	3037	2	784	1243	1795	2713	3882	3461	388
Max.	807,08	5,70	108,47	606,56	3140,75	1599	3180	20	2964	5223	5777	6955	8600	7892	7052

Analyzing table 2 and visualizing the classification regarding the levels of degradation and precipitation, it can be seen that there is an inconclusive situation between the levels, there was no linearity of the values. So, by themselves, it is not possible to conclude that they were representative for the construction of the index. The LS factor had almost no variation between classes and DEM and slope increased as the degradation level increased since where the relief reaches higher altitudes, it is also where it has higher values of declivity. In relation to the spectral bare soil image, the amount of clay influences the reflectance of the soil, which causes the increase of values according to the decrease of clay and the consequent increase of the levels. In the SF case, it increases as the level goes to 3 and then decreases to the 5. This may have happened due to the greater dissemination of conservationist tillage practices with soil cover using straw, green manure and others, mainly in places at greater risk of degradation, which can force farmers to take measures to better conserve their areas. As already mentioned, CEC and clay were the parameters to define the degradation classes, so the higher the value of these variables, the lower the degradation level.

The highest values of SDI were found in the center and southwest of São Paulo state (Fig. 9), occurring mainly in sandy soils of low CEC and OM. Low CEC and OM values are related to lower biomass production, which is also affected by the lower water retention capacity of sandy soils. Sugarcane production, in these types of soils, has lower average productivity (Landell et al., 2003; Sanches et al., 2019), which entails the need to renovate cultivated areas, requiring soil tillage, a practice that cooperates with the mineralization of SOM. Pastures in these areas in general are in some degree of degradation, which accentuates the low coverage of the surface, increasing erosion problems (Merten and Minella, 2013).

There is a consensus in the literature that the removal of crop residues causes impacts on the soil that, if not well managed, can negatively alter its functions (Karlen et al., 2019, Freixo et al., 2002). Carvalho et al. (2019), found that for sugarcane, indiscriminate straw removal can have detrimental effects on soil functions. Furthermore, Lehmann et al. (2020) also agree that several factors are capable of influencing the soil response in terms of susceptibility to degradation. Therefore, it is important to recognize and compute differences in topography, climate, soil and impacts that different forms of management have, for better decision-making on which strategies to use in the desired location.

The observations about the reflectance of the bare soil composite image bands are in agreement with Demattê et al. (2009). The values obtained show low reflectance intensity in bands 1 and 2, increasing in 3 and 4 reaching a maximum in 5, and decreasing again in 7. All values occurred in the same way, varying in the increase of the intensity. The clayey soil, for example, follows a trajectory of less intensity of reflectance (fig. 9b) in which as the level of degradation grows (indicating the decrease of clay amount), the reflectance of the bands also tends to increase.

The validation of SDI with OM showed a negative correlation, which is the higher the SDI, the lower the amount of organic matter (Fig. 9a). The OM is an indicator of soil quality and one function that can be nominated is biomass production. Thus, this was a satisfactory result, since more degraded areas are the ones that have less organic matter.

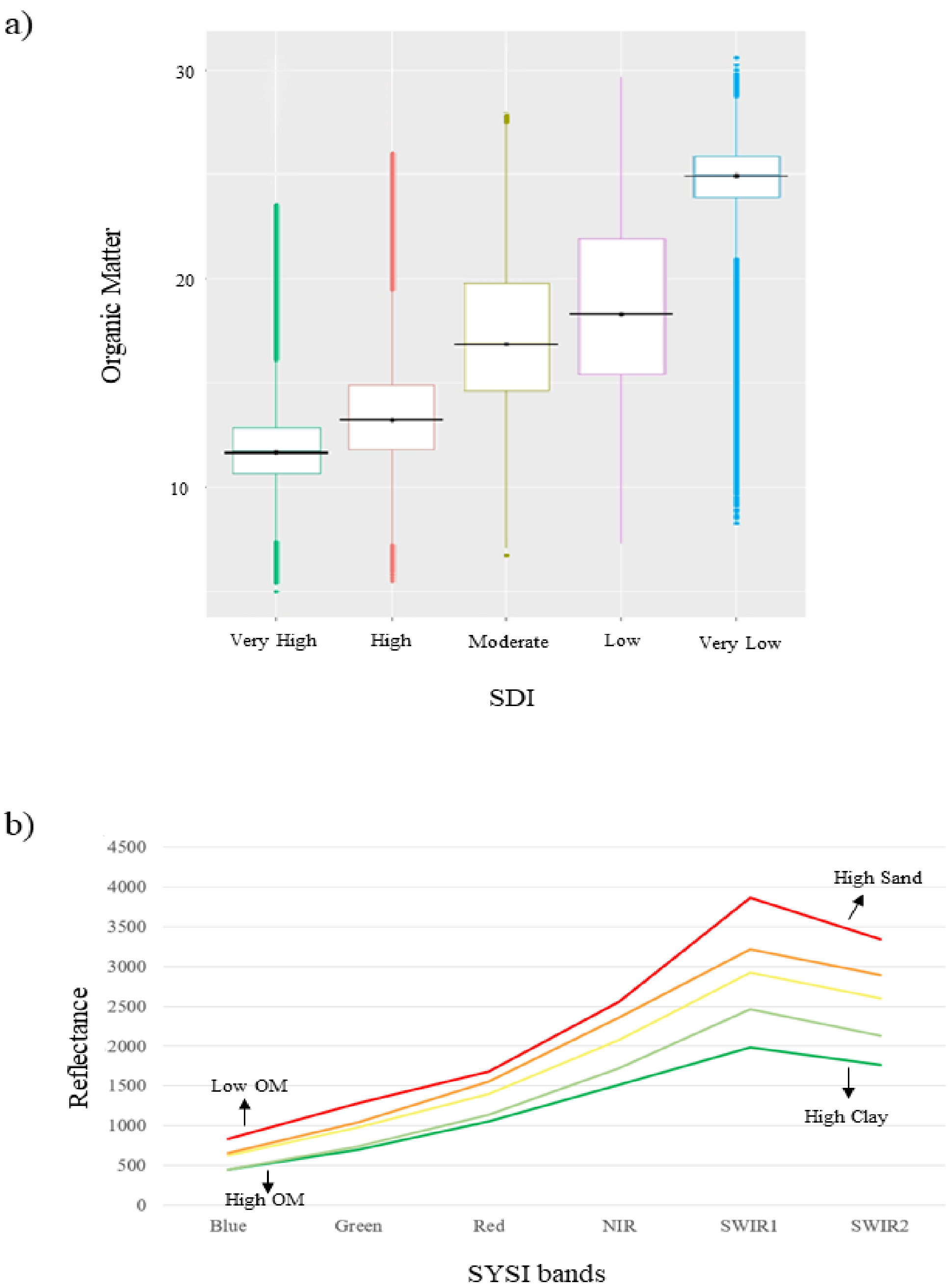

Figure 9. a) Boxplot of the interaction between the Soil Degradation Index (SDI) and the Organic Matter. b) Levels of degradation associated with spectral curve.

The bare soil frequency (Fig. 2b) showed high soil exposure variability across the study area. When comparing the SF with LULC (Fig. 7), it is possible to observe that the agricultural and pasture areas presented greater soil exposure, with a frequency of 500 to 1100 times of soil exposure. There is a perception that human activities are exposing the soils and leading to degradation (Medeiros et al., 2016; Merten and Minella, 2013). However, Demattê et al., (2020), showed that there has recently been an increase in the adoption of conservation practices in Brazilian agricultural areas, creating a tendency to decrease the frequency of soil exposure in these areas.

In Medeiros et al. (2016) study, the authors estimated the annual soil loss rate in the state of São Paulo. They also found that many areas of the state have high levels of soil degradation, especially in sugarcane and pasture use. Another problem duly pointed out is that improper land management in previously productive areas causes its abandonment due to degradation, mainly caused by the erosion process. However, according to Cunha et al. (2016), the expansion of agricultural areas over degraded pastures can reduce the risks of soil erosion by up to 20%.

Another research carried out in the same region with the objective of evaluating the soil degradation level by water erosion, demonstrates that several areas in the state reached a very critical level of soil depletion, due to the predominance of agricultural activities, mainly sugarcane and livestock farming (Medeiros et al., 2016).

In order to make a brief comparison with one more factor, we used the Instituto Florestal (Forestry Institute) pedological map. The predominant soil class in the study area is Ferralsols, covering 38.14% of the state, followed by Lixisols, covering 37.63% (Rossi, 2017). By covering an extensive area with different local specificities, both soils that alone cover more than half of the state, are present from the highest level of risk of degradation to the lowest level. Thus, in a general panorama, it was not possible to find more details that correlate these two objects.

Dube et al. (2017), also stated that determining the distribution of vulnerable areas with levels of degradation by associating various factors is valuable for coming up with possible control measures and strategies plans. It is expected that by the year 2037, more than 300,000 restoration projects will be carried out in the state of São Paulo (Chaves et al., 2015). Therefore, we hope that this method, developed with the use of satellite images and environmental data, will be useful in the application of these programs, considering the agility for monitoring large areas.

4 CONCLUSION

The development of a degradation index map based on environmental variables was achieved. The Clay and CEC content were used in order to designate the levels of degradation, working in a good sense. The insertion of remote sensing co-variables i.e., surface temperature and bare soil had a positive correlation with SDI. The organic matter had a negative correlation with the index and ratified the consistency of the index with great accuracy. Also, spectral data gave important clue on its relationship with the SDI since low SDI areas presented low spectral intensity related to higher organic matter. The high level of SDI was the most representative in the study area and the very low level was the least present. These statements show a good modeling of the index, since SDI had an inverse proportion with an indicator of soil health. Research and methods to assess the soil degradation must be increasingly robust in order to monitor and control the soil quality. Remote sensing appears to be a promising technology. Using satellite images for digital soil mapping and monitoring is an important tool to analyze the dynamics in land use changes, which can lead to soil losses resulting in economic and environmental issues. Thus, may bring light for better decision making aiming for the good practices to manage the land as for public policies.

For future work, some following recommendations are made. It is interesting to develop the degradation of each period, analyze the trend of improvement and relate it to the effectiveness of public policies. Knowing the awareness of farmers about the importance of better forms of soil management can be a good tool to develop mechanisms aiming to spread the knowledge of studies such as this. Also, it is relevant to understand the specificities of each locality over time to develop more effective management plans.

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