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C-factor Estimate for Soil Loss Equations Using Transformation Function (Near, Gaussian and Symmetric Linear) and Remote Sensing data†

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Abstract: The study proposes a methodology to calculate the C-factor using remote sensing data: NDVI from LANDSAT image and MAPBIOMAS Land Use (LU) classification to Atibaia river watershed, Brazil, to improve the estimation of risk of soil loss using equations such as USLE and RUSLE. The methodology follows the procedures: first the NDVI was calculated, then the resulting image was rescaled to the range 0 to 1, applying the Near, Gaussian and Symmetric Linear transformation functions, with value below threshold 1, value above threshold 0 and scale 1 in the Rescale by function tool. Among the three models presented the Symmetric Linear model showed the best results for the distribution of C-factor values between the LU classes, while in the Gaussian model the same value was recorded, 0.70, for the Pasture and Rocky Outcrop classes and the average of the values was low 0.22 (Near) and 0.31 (Gaussian).

Keywords: soil erosion; C-factor; NDVI; transformation function; land use

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1. Introduction

Soil erosion is a process that occurs in different areas of the planet. Inadequate land use through non-conservation practices increases susceptibility to this process.

To identify and quantify the areas affected by this process, soil loss models such as Universal Soil Loss Equation (USLE) and Revised Universal Soil Loss Equation (RUSLE) can be used. To calculate these models, C-factor (Crop Management) is needed, used to determine the effectiveness of soil and crop management systems in preventing soil loss resulting from erosion by rain. This factor represents the soil loss ratio between an area with preserved vegetation cover and management and an area with plowed and bare soil during the cultivation period [1].

Vegetation cover can be analyzed using spectral indices obtained by radiometric measurements from satellite images. The red and infrared bands are the most sensitive to the biophysical variations of vegetation over time and space. Among the most used spectral indices is the Normalized Difference Vegetation Index (NDVI). This index uses the red bands and varies from -1 to 1. The studies by [2,3] use the NDVI to calculate the C-factor, [1] uses the NDVI to calculate the C-factor in the Atlantic Rainforest of Brazil.

There are few studies [1], that used spectral indices to calculate the C-factor in Atlantic Rainforest area, where intense land use and climate favor erosion [4,5]. Due to the scarcity of methodologies that use spectral indices to calculate the C-factor, the literature review and the use of analog cartographic bases of use and coverage are still very present in studies developed to calculate the C-factor in Atlantic Rainforest area, such as Brazil. The use of spectral indices derived from satellite images, using remote sensing, is a possibility to reduce data collection costs, in addition to enabling faster and more accurate data analysis that supports assessments of changes in land use and land cover, degradation of soils, and erosion prevention [3,6–8].

Due to the scarce scientific production on the calculation of the C-factor in areas of the Atlantic Rainforest, a region intensely occupied throughout the 19th and 20th centuries that potentiated erosion processes in this region [9], we propose a methodology based on remote sensing and GIS to calculate the C-factor using the transformation functions (Near, Gaussian and Symmetric Linear), apply in the Atibaia watershed, São Paulo State, Brazil.

2. Material and Method

2.1. Study Area

The Atibaia river basin is located between two metropolitan regions of the State of São Paulo, the Metropolitan Region of São Paulo (RMSP) and the Metropolitan Region of Campinas (RMC), in addition to the source of important rivers that form it, located in Atlantic Rainforest of Brazil. Cantareira System, the region with reservoirs responsible for supplying water to the population of the RMSP (Figure 1).

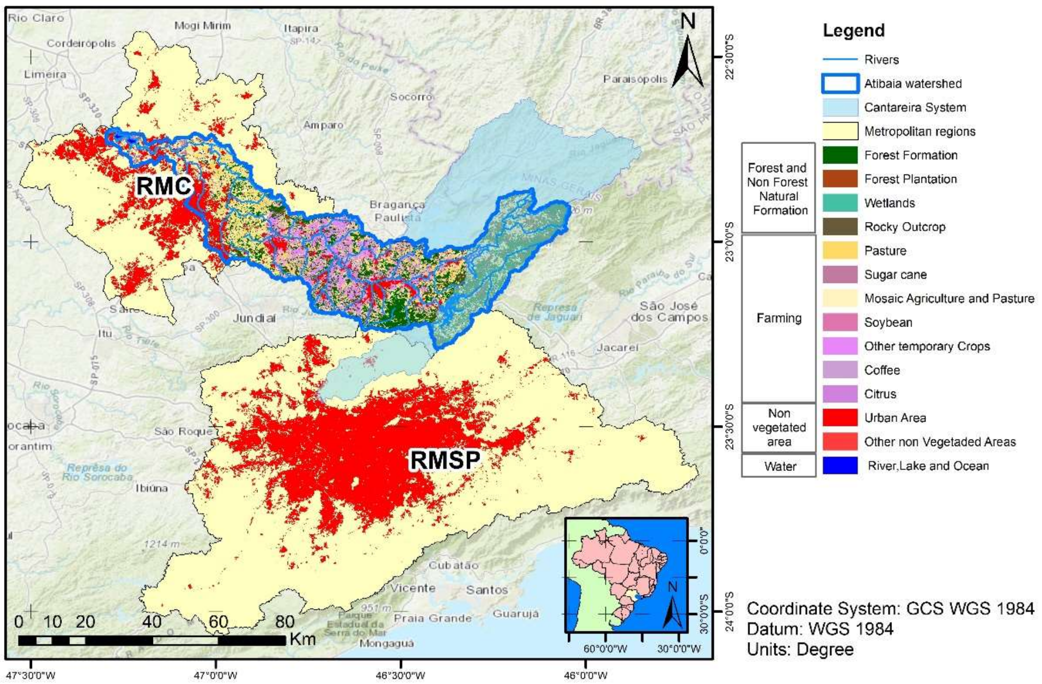

Figure 1. Study area. Source: Organized by the authors.

The areas cover 276.849 ha, in a region with a high concentration of population, agricultural areas and a water system with important hydrographic basins that have been intensely modified over time due to altars resulting from land use and cover.

2.2. Data Acquisition and Processing

The test with the transformation functions was applied to a LANDSAT-8 image from July 2, 2014, acquired at the EarthExplorer. In the years 2014–2015, the state of São Paulo experienced a prolonged drought. The periods of severe drought in recent years and dependence on the Cantareira System for supply the two metropolitan areas, it results in a worrying long-term prognosis for water security and water governance [10,11].

The image underwent necessary radiometric corrections and then the NDVI formula proposed by [12] was applied:

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

The IV represents the infrared band and the V represents the red band. After calculating the NDVI, a mask was created to remove negative values.

In the next step, the C-factor was calculated using the Near, Gaussian, and SymLinear transformation functions. In this step, the NDVI values were rescaled using a mathematical function using the Rescale by function tool in ArcGIS. The parameters defined for calculating the Near, Gaussian, and SymLinear transformation functions were: value below threshold = 1, value above threshold = 0, from scale = 0, to scale = 1, and the transformation functions: *Near* is most useful if the highest preference is near a specific value, *Gaussian* the transforms the input values using a normal distribution and *SymmetricLinear* (SymLinear) applies a linear function between the specified minimum and maximum values which is mirrored around the midpoint of the Minimum and Maximum. The Near and Gaussian transformation functions can be similar, depending on the specified parameters. The Near function generally decreases at a faster rate, with a narrower spread, than the Gaussian function.

With the three calculated functions, we extract the C-factor values of the different models (Near, Gaussian and SymLinear) by land use class using a sample of random points of 644 observations. In this sample we apply the *tapply* function in Rstudio, extracting the minimum, maximum, average, and median values by LU classes from the mapping developed by Mapbiomas platform[1] (2014 image).

3. Results and Discussion

Figures 2 and 3 shows the distribution histograms and NDVI images and the three proposed models:

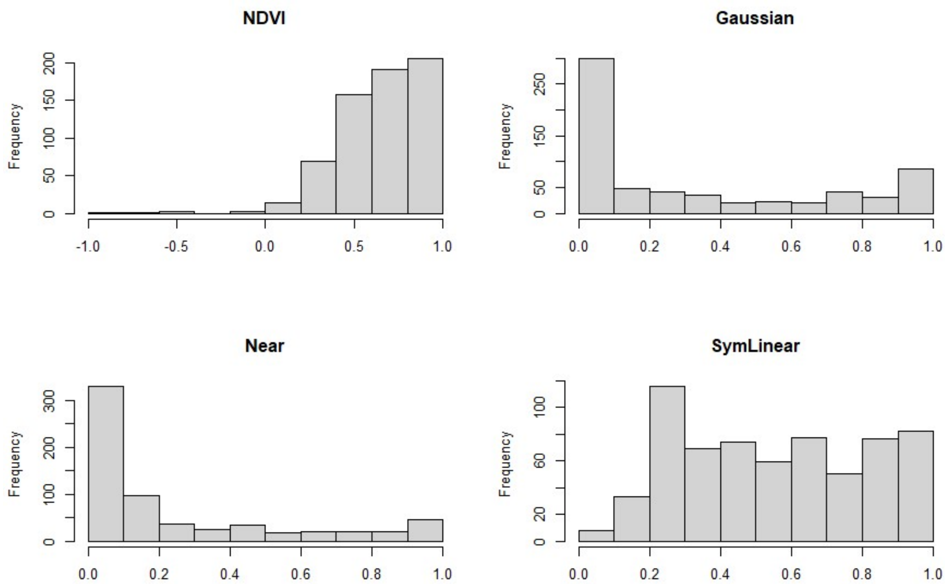

Figure 2. NDVI and C-factor models histograms. Source: Organized by the authors.

1. https://mapbiomas.org/

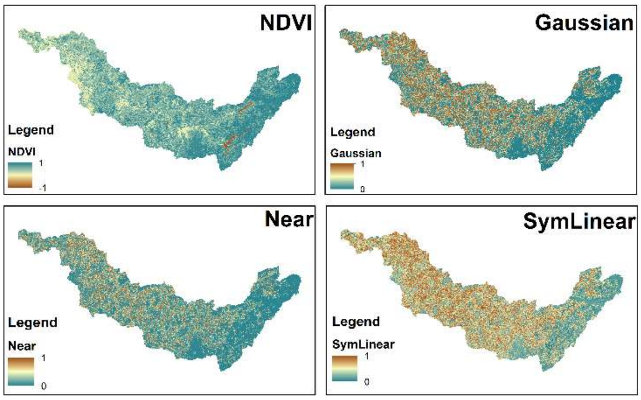

Figure 3. NDVI and C-factor models images results. Source: Organized by the authors.

In the Atibaia watershed, a large number of pixels with NDVI values above 0.5 are found, indicating that the vegetation cover is high. Among the three proposed models, it is identified that the classification of the Gaussian and Near models concentrated a large number of pixels with lower values, between 0 and 0.2. While the SymLinear model better distributed the values between the range 0 and 1.

The minimum, maximum, mean and median values of three transformation functions by LU classes are (Table 1):

Table 1. Statistics models results. Source: Organized by the authors.

		Gaussian				Near				SymLinear			
	Area (ha)	**Min**	**Median**	**Mean**	**Max.**	**Min**	**Median**	**Mean**	**Max.**	**Min**	**Median**	**Mean**	**Max.**
Forest Formation	83 520.14	0.001	0.010	0.054	0.996	0.010	0.026	0.055	0.984	0.142	0.291	0.331	0.979
Forest Plantation	10 671.40	0.001	0.002	0.039	0.982	0.008	0.013	0.048	0.933	0.127	0.181	0.223	0.956
Pasture	46 341.74	0.054	0.767	0.693	0.999	0.055	0.477	0.516	0.996	0.437	0.830	0.808	0.990
Sugar cane	2 837.97	0.406	0.758	0.716	0.944	0.199	0.469	0.487	0.810	0.687	0.827	0.815	0.921
Mosaic Agriculture and Pasture	54 207.68	0.006	0.238	0.362	0.999	0.021	0.128	0.264	0.998	0.251	0.605	0.627	0.992
Urban Area	32 182.93	0.000	0.396	0.446	1.000	0.000	0.195	0.326	1.000	0.005	0.683	0.652	0.998
Other Non-Vegetaded Areas	635.72	0.008	0.063	0.084	0.181	0.024	0.059	0.063	0.106	0.277	0.453	0.433	0.569
River,Lake and Ocean	4 671.58	0.000	0.000	0.160	0.992	0.000	0.000	0.130	0.968	0.000	0.000	0.192	0.970
Other temporary Crops	41 460.88	0.009	0.432	0.491	1.000	0.025	0.212	0.348	1.000	0.287	0.698	0.701	0.997
Citrus	110.11	0.200	0.200	0.200	0.200	0.113	0.113	0.113	0.113	0.582	0.582	0.582	0.582

In all LU classes, the SymLinear model obtained higher average values concerning the Gaussian and Near models. The three models maintained the same pattern of distribution of mean values in the LULC classes.

In two LU classes, the values of Gaussian and Near models mean are very similar. In the Forest Formation class, the mean values are 0.054 (Gaussian) and 0.055 (Near). In the Forest Plantation class, the mean values are 0.039 (Gaussian) and 0.048 (Near).

The same pattern is observed between the Citrus and Coffee classes; Pasture and Rocky Outcrop; Wetlands and Other Non-Vegetated Area. While the other classes recorded values with good separability between them.

The dense vegetation classes were the ones that registered the lowest values in all models. While the classes related to agricultural plantations registered intermediate values, which are related to the type of culture and its stages of development [13,14]. The classes related to pastures and Rocky Outcrops registered the highest values. This is due to the exposure of these classes to the weather that results in erosive processes and consequent loss of soil [15].

4. Conclusions

The use of NDVI to calculate the C-factor in soil loss equations is a widely used method, as addressed by the studies of [1–3]. In the present study, we seek to present three other models based on transformation functions, classifying of NDVI images, according to the Gaussian, Near, and SymLinear functions.

The study also proposes the calculation of the C-factor using only a selected satellite image for the 2014 dry period and not the average calculation of the C-factor as proposed by Durigon [1]. This date was selected due to the occurrence of an extreme drought event recorded in the Atibaia watershed. In this way, it was possible to identify the real photosynthetic activity of the vegetation, which is not possible when calculating an average NDVI image of a period.

Knijff [2] pioneered study the estimation of the C-factor using the NDVI for European conditions. New studies proposing methodologies for other regions of the planet are needed. The study area of this article is located in the Atlantic Rainforest, with scarce publications on the subject and intense modification of use and coverage, due to economic growth, importance of agricultural activity and the Atibaia watershed being used for public supply of a region with high population density, formed by the RMC and RMSP in the State of São Paulo, Brazil [16–19]. These characteristics in a scenario of climate change, with extreme drought events as registered in 2014 [11,16], increase the vulnerability of the Atibaia watershed. Studies like this one, developing methods to estimate the C-factor, help in the development of studies to estimate soil loss in Atlantic Rainforest.

We apply transformation functions and correlate them with land use and land cover classes. We observed that the Near and Gaussian functions recorded similar values. This is because the two functions register the same pattern of distribution of values, depending on the parameters. Neighboring pixels had a greater influence on the distribution of values in these two functions. While at SymLinear applying a linear function that considers the minimum and maximum values, it resulted in a more balanced distribution in the adopted scale. Thus, the separability of the C-factor values by land use class was better used.

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