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Effects of DEM resolution on the RUSLE-LS factor and its implications on soil and water management policies through the land cover seasonality

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This study aimed to demonstrate the effects of spatial resolution in modeling water erosion by the Revised Universal Soil Loss Equation (RUSLE). In this study, three specific objectives were defined: Evaluation of the effect of the geographic information source on water erosion, seasonal effects on the potential production of sediments, as well as public policies concerning the different scenarios. The topographic factor (LS) of this equation was determined using four digital terrain models, with different spatial resolutions (10 and 30 m). The results of this factor prove to be influenced by the resolution of the DEM used. The spatial modeling of water erosion was carried out by combining the various input variables of the RUSLE model. The analysis of the obtained erosion maps revealed that its production is influenced by the spatial resolution and by the seasonality, demonstrating that the DEM obtained via DRONE presented the lowest values of soil loss potential in any scenario. Thus, it was verified a need to implement practices for the management of soil cover and conservation to reduce vulnerability to water erosion in the watershed.

Key words: Soil erosion, geographic information system (GIS), watershed, modeling, hydrology.

INTRODUCTION

Soil erosion is characterized as a natural and continuous phenomenon, which may occur to a greater or lesser extent, depending on the degree of association between various factors, such as relief, climatic conditions represented by the intensity of rain, dynamics of water movement in the soil (infiltration and redistribution processes), soil type (texture, hydraulic permeability, porous continuity), and land use and occupation (expansion of agricultural frontiers, waterproofing of urban areas and demographic growth). According to Lepsch (2010), the combinations of these factors lead to ecological and economic losses.

The accelerated erosive process causes changes in the surface runoff and, consequently, in the hydrological dynamics of the watershed, with effects on the decrease of water availability in periods of drought, increased peak flow in the rainy period with a propensity to flooding generation, silting up watercourses, besides the impacts

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on water quality (Nunes and Roig, 2015; Botelho et al., 2018), and also increasing public spending in an attempt to reverse or mitigate this environmental imbalance.

According to Souza Júnior et al. (2017), the current Brazilian model of water management contributes to the increase of problems associated with water scarcity, which becomes necessary to improve the articulation mechanisms between water resources plans with the use of integrated assessment tools, and among these tools, the mapping of the areas most susceptible to erosion.

These tools, therefore, allow the construction of much more effective risk management (Vörösmarty et al., 2010; Kirchhoff et al., 2013), based on the use of hydrological modeling, contributing to improving the efficiency of public spending and management activities of the watershed, since management practices are directly dependent on the estimated soil loss (Ganasri and Ramesh, 2016).

The use of mathematical models for this purpose is essential due to the operating costs for direct measures in large areas, which become impractical from a financial point of view; methodological restrictions and, mainly, the time to obtain the information (Panagos et al., 2015; Rodrigues et al., 2017).

According to Karydas et al. (2014) and Hrabalíková and Janeček (2017), among the more than 80 models currently in existence to estimate potential soil erosion, varying in time and space scales, the models of the USLE family are still the most used. The revised universal soil loss equation - RUSLE (Renard et al., 1997) aims to estimate water erosion from climatic, pedological, and topographic variables, besides the conditions of use, management, and soil conservation practices.

According to Minella et al. (2010), the topographic factor (LS) represents the dynamics of surface runoff in the erosion process in the studied area. Its determination has limitations due to the complexity of the relief, resulting in erroneous estimates of erosion rates, leading to the need to incorporate the concepts of unit stream power (Yang, 1972), associated with the accumulated flow (Desmet and Govers, 1996) and geoprocessing techniques.

Thus, according to Zanin et al. (2017), the accuracy of erosion modeling is based on the ability to be able to explain the physical factors that determined the output result and on the accuracy of each physical factor of input. In this way, the results obtained will have a significant impact on the need to prevent natural disasters due to erosion processes.

In this sense, spatial resolution can have significant effects on soil loss assessment models (Datta and Schack-Kirchner, 2010), and their choice must be guided to reduce errors in topographic attributes (Wu et al., 2005), which allows a better analysis of the assessed area and, consequently, in the development and improvement of watershed management and conservation policies by management committees.

Considering that there is a growing demand for information on environmental impacts, whether resulting from agricultural, industrial activities or urbanization processes on water resources, this work aims to evaluate the effects of spatial resolution in determining the LS factor of RUSLE in a watershed located between the second and third plateau of Paraná. And, also its effect on the potential estimate of erosion based on the seasonal variation of land use and occupation, considering the central months of the seasons and how this information can impact soil management and conservation from a perspective development of public policies.

MATERIALS AND METHODS

Study area

The study area is in an affluent micro watershed of the Pitangui River with a total area of 604.9 ha. This watershed belongs to the watershed of the Tibagi River, in Castro - PR (Figure 1), inserted in the region called Campos Gerais, with a predominance of Latossolo Bruno Ácrico (LBw2) according to survey and soil recognition in the State of Paraná. This region stands out for grown of soybeans, corn, and beans, and it is considered one of the most important milk-producing regions in the country.

Maps database

The mapping of land use and cover considered the central months of the seasons, to be able to assess the effects of seasonality in the estimation of sediment production by the watershed, as well as the effect of anthropogenic dynamics in it. For this, four images obtained from the ESA base of the Sentinel-2 satellite were selected, with a spatial resolution of 10 m and, subsequently, their supervised classification was performed, obtaining the distribution of use as shown in Table 1, generating maps in the scale of 1: 25,000 (Figure 2).

Four databases were used to generate different digital elevation models with their respective spatial resolutions. The first DEM was obtained from an SRTM image prepared by the USGS with a resolution of 30 m (LS1), made available by the Instituto Nacional de Pesquisas Espacias - INPE (National Space Research Institute) through the TOPODATA project. The second DEM was based on contour lines provided by the Laboratório de Pesquisas Aplicadas em Geomorfologia e Geotecnologia - LAGEO-UFPR (Laboratory for Applied Research in Geomorphology and Geotechnology) with a resolution of 10 m (LS2). The third DEM from the database was made available by the Instituto de Terras, Cartografia e Geociências do Paraná - ITCG (Institute of Lands, Cartography, and Geosciences of Paraná), also with 10 m resolution (LS3). And, the fourth DEM was produced from an unmanned aerial vehicle image (DRONE), where the contour lines were extracted through aerophotagrametry, with a resolution of 10 m (LS4).

Potential soil loss estimation

The RUSLE was structured in a GIS environment, allowing the generation of individual and spatial maps of each component of the model aiming to develop the identification map of the area’s most vulnerable to water erosion, varying the spatial resolution and consequently the topographic factor and, the use of the soil from

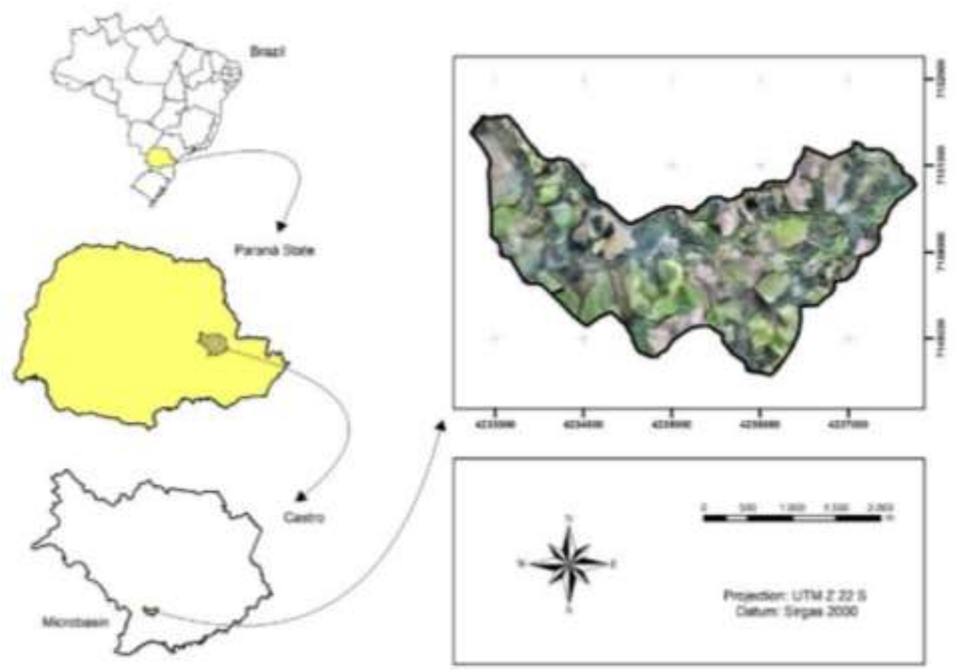

Figure 1. Location map of the study area.

Table 1. Percentage distribution of classes of use relative to central months.

Data	Land cover	Area (ha)	% Distribution	Total (ha)
January 5th, 2018 (Summer)	Annual cropping	260.35	43.04	604.9
	Native forest	216.92	35.86	
	Fallow agriculture	65.57	10.84	
	Pasture land	61.94	10.24	
	Dirt road	0.12	0.02	
April 13th, 2018 (Autumn)	Annual cropping	93.28	15.42	604.9
	Native forest	203.13	33.58	
	Fallow agriculture	164.17	27.14	
	Pasture land	144.21	23.84	
	Dirt road	0.12	0.02	
July 18th, 2018 (Winter)	Annual cropping	117.77	19.47	604.9
	Native forest	203.13	33.58	
	Fallow agriculture	102.05	16.87	
	Pasture land	181.83	30.06	
	Dirt road	0.12	0.02	
October 30th, 2018 (Spring)	Annual cropping	38.47	6.36	604.9
	Native forest	203.00	33.56	
	Fallow agriculture	278.56	46.05	
	Pasture land	84.75	14.01	
	Dirt road	0.12	0.02	

the representative images of the central months of the climatic seasons (January, April, July, and October). Then a linear combination of the factors that characterize erosion was performed, according to Equation 1:

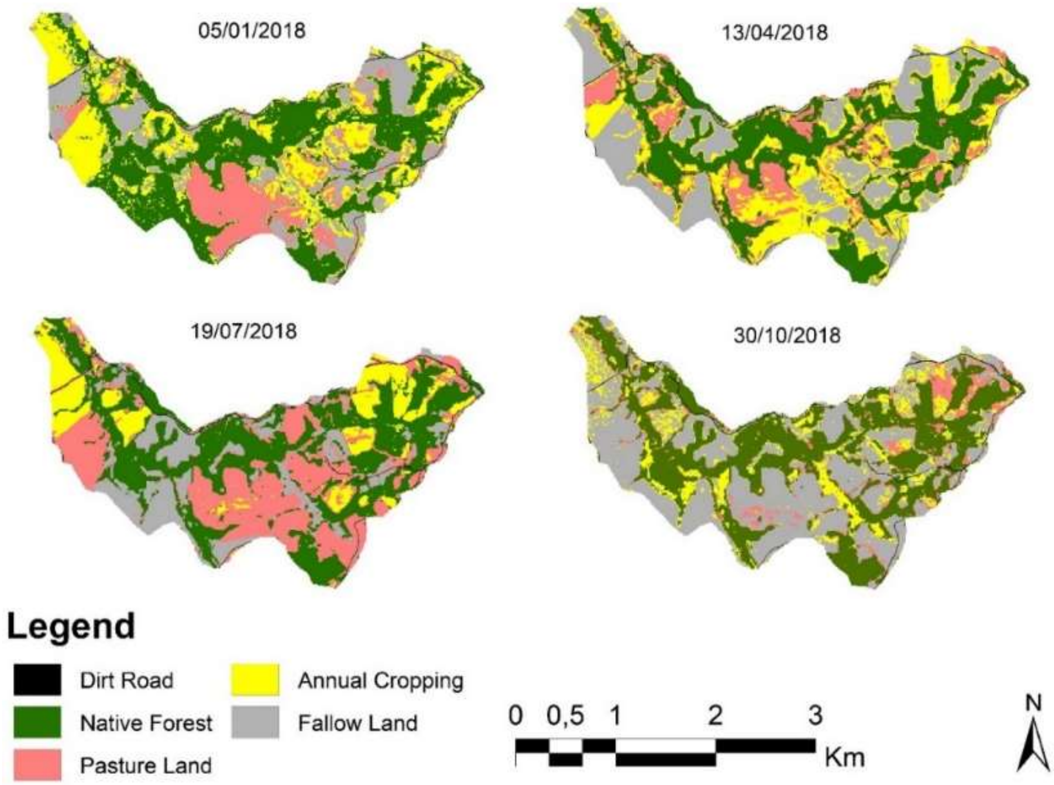

Figure 2. Land use classification map for the central months of the climatic seasons.

$$A = R \cdot K \cdot LS \cdot C \cdot P \tag{1}$$

where A represents the average annual rate of soil erosion per unit area (t ha^{-1} year^{-1}); R is the average annual rainfall erosivity factor (MJ mm ha^{-1} h^{-1} year^{-1}); K is the factor corresponding to soil erodibility (t ha MJ^{-1} mm^{-1}); LS is the topographic factor represented by the length and slope (dimensionless); C corresponds to the soil cover factor (dimensionless), and P is the factor associated with conservationist erosion control practices (dimensionless).

Rain erosivity

Erosivity represents the potential of rain to cause erosion due to the detachment of solid particles due to the kinetic energy of the rain. For the state of Paraná, research aimed at estimating this parameter began in the 1980s, as shown by Netto et al. (2018), with emphasis on the works of Castro Filho et al. (1982), Rufino (1986), Rufino et al. (1993), and Waltrick et al. (2015).

However, even in the condition highlighted earlier, the annual erosivity map for the watershed may not represent the necessary spatial distribution, and unique R values end up being used to characterize an entire watershed. In this sense, it was decided to use a multivariate statistical model, developed by Mello et al. (2013), in which it is proposed to estimate the average annual erosivity as a function of the latitude, longitude, and altitude of each cell in the watershed, allowing to characterize in a distributed way the rain erosivity. It should be noted that this model has been widely used, according to the studies by Oliveira et al. (2014a, b), Rodrigues et al. (2017), Steinmetz et al. (2018), among others. The model developed by Mello et al. (2013) for the southern region of Brazil is as follows:

$$R = 2610770 - 60.44 \cdot A + 98839 \cdot LO - 1114.68 \cdot LA^2 + 938.47 \cdot LO^2 - 1.182 \cdot A \cdot LO$$
$$+ 1.1885 \cdot LA^2 \cdot LO^2 + 0.01494 \cdot LA^2 \cdot LO^3 \tag{2}$$

where R is average annual erosivity (MJ mm ha^{-1} year^{-1}), A is altitude (m), LA corresponds to latitude, and LO refers to longitude, both in negative decimal degrees.

Soil erodibility

Erodibility represents the soil's intrinsic vulnerability to erosion, due to the ease of detachment of solid particles by the impact of the raindrop. This factor can be estimated by different methodologies. According to Marques et al. (2019), one of the alternatives to measure the K factor is from direct measurements in experimental fields under natural or simulated rain, however, under these conditions the estimate becomes costly and time-consuming, even considering the standard method (Lin et al., 2019). Besides this methodology, erodibility can be estimated using pedotransfer function, which uses multiple regression models (Young and Mutchler, 1977; Bertoni and Lombardi Neto, 2005; Marques et al., 2019).

On the other hand, Marques et al. (2019) report that for countries like Brazil, the determination of this parameter is hampered by costs and, therefore, the use of predefined values for some soil classes are commonly used (Beskow et al., 2009). Thus, as the watershed has a ruling class of soils (Latossolo Bruno Ácrico), the value adopted was 0,018 t h MJ^{-1}mm^{-1}, according to Albuquerque et al. (2000).

Table 2. Classes of topographic factor LS.

LS	Class
0 - 1.2	Very low
1.2 - 1.7	Slightly low
1.7 - 3.3	Low
3.3 - 5.5	Moderate
5.5 - 7.5	Moderately high
7.5 - 20	High
> 20	Very high

Table 3. C values for coverage and land use conditions.

Land use	C-factor	Source
Annual cropping	0.253	Bertoni and Lombardi Neto (2008)
Native forest	0.012	Farinasso et al. (2006)
Fallow land	0.5	Panagos et al. (2015)
Pasture land	0.015	Tomazoni et al. (2005)
Dirt road	1	-

Topographic factor

Ahamed et al. (2000) showed that the effect of slope length and its gradient on the erosion process intensity could be determined with the aid of a GIS and in watershed scales, by combining a digital elevation model of the terrain (DEM) with processing algorithms to obtain the cell length and slope in a distributed way.

In the particular case of RUSLE, the calculation of the LS factor incorporates a vital concept associated with the contribution of surface runoff from upstream to downstream, giving a more appropriate physical interpretation to the erosive process than that adopted in the calculation by USLE.

The procedure presented by Moore and Burch (1986) via GIS and equation proposed by Zhang et al. (2013) and Abdo and Salloum (2017) was adopted and used to estimate the value of the LS factor, according to Equation 3.

$$LS = \left(\frac{FA \cdot CS}{22.13}\right)^{0.6} \cdot \left(\frac{\sin(S) \cdot 0.01745}{0.09}\right)^{0.6} \quad (3)$$

where FA is the flow accumulation expressed as the number of grid cells, CS is the raster spatial resolution (m), and S is the slope in degrees.

The LS factor explains the effect of topography on erosion by RUSLE and is calculated as the product slope length sub-factor (L) and slope sub-factor (S). These two subfactors combined represent the ratio of soil loss at a given length and slope of any point from a slope of the unit that has a length of 22.13 m and a slope of 9%, where all other conditions are the same. Thus, the values associated with the LS are not absolute but reference to the value of 1. If <1.0, it represents areas less erosive than the standard reference condition. If > 1.0, it represents more erosive conditions than the aforementioned reference (Yang, 2015).

The proposal made by Ruthes et al. (2012) was adopted to classify the LS factor, which adapted the classification by Fornelos and Neves (2007), and it is presented in Table 2.

Erosion control practice factor (P) and cover management factor (C)

Factor P represents management practices that contribute to erosion control. However, due to the difficulty in identifying such practices through satellite images, it was decided to adopt their value equal to 1, as seen in similar works, especially those of Vemu and Pinnamaneni (2011), Pradhan et al. (2012), Silva et al. (2012), Oliveira et al. (2014), Bera (2017), and Steinmetz et al. (2018).

Factor C represents the conditions that can be easily changed to contain soil erosion, ranging from 0 to 1, where values close to 1 indicate areas with almost null vegetation cover and, therefore, more susceptible to water erosion. The classes of use were defined, as well as their percentage of occupation (Table 3) using satellite images of the central months of the climatic seasons. Then C values were adopted according to studies published for the same uses in Brazil, which are shown in Table 3.

RESULTS AND DISCUSSION

About the DEMs produced by the different databases, variations were observed concerning the altitudes between the models, based on the layout of the topographic dividers initially obtained from the LAGEO-UFPR base.

The DEM generated from DRONE showed values that ranged from 930.49 to 997.86 m, with an image of 60,490 pixels and a resolution of 10 m. The image obtained via SRTM, in turn, had an elevation ranging from 939.22 to 1022.66 m, with approximately 6,910 pixels and a resolution of 30 m. Considering the LAGEO-UFPR and ITCG bases, both with a spatial resolution of 10 m and 60.490 pixels, a small difference was observed, the first

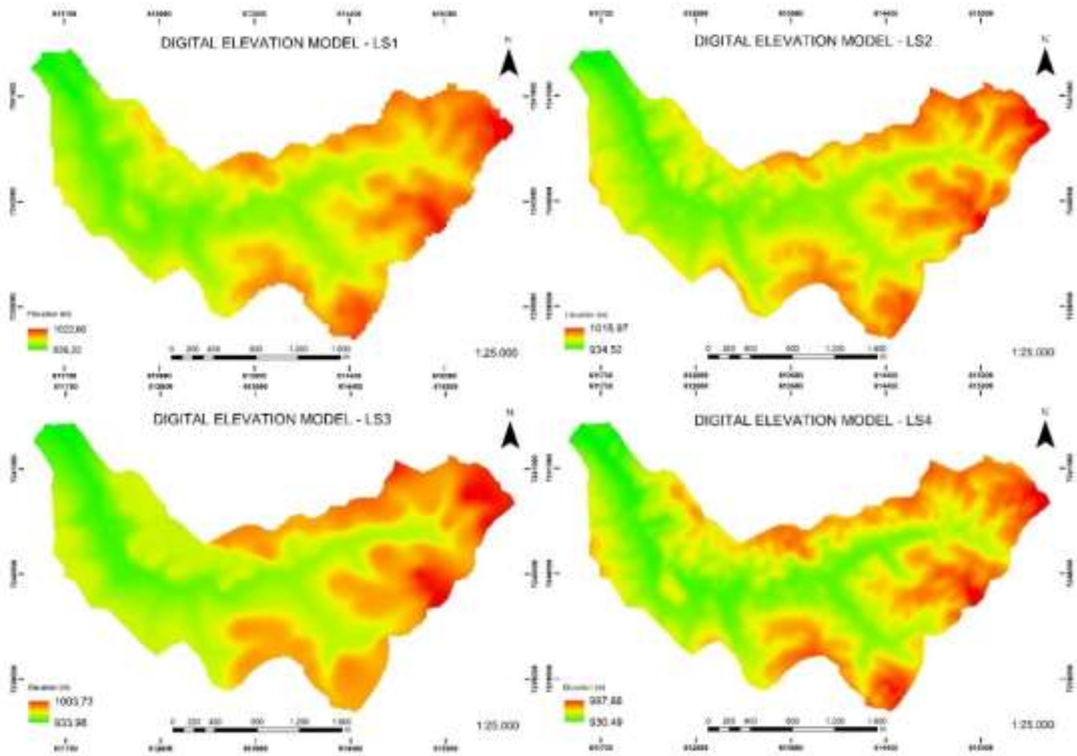

Figure 3. Digital elevation model from the bases SRTM, LAGEO, ITCG, and from the DRONE.

Table 4. Classes for the LS factor.

Classification	LS1	LS2	LS3	LS4
	(ha)			
Very low (0 - 1.2)	234.99	455.05	413.42	556.52
Slightly low (1.2 - 1.7)	84.33	67.74	96.53	19.35
Low (1.7 - 3.3)	174.87	59.9	79.86	16.78
Moderate (3.3 - 5.5)	75.15	16.56	10.16	7.28
Moderately high (5.5 - 7.5)	19.44	4.46	2.95	2.67
High (7.5 - 20)	29.88	1.22	1.98	1.44
Very high (>20)	3.24	-	-	0.04

had altitudes between 934.52 and 1015.97 m, and the second had altitudes between 933.98 and 1003.73 m, as can be seen from the analysis of Figure 3.

It verifies that in both maps, it is in the northeastern portion that the highest topographic elevations are concentrated and, such differences between altimetric values, can lead to an increase in the values of the LS factor and, consequently, in the production of sediments from the watershed (Figure 3).

Once the DEMs were obtained, flow accumulation maps were generated, thus allowing the application of Equation 3 to obtain the LS factor. Once the LS maps were generated, the classification proposed by Ruthes et al. (2012) was followed, which was adapted from the classification initially proposed by Fornelos and Neves (2007) (Table 4).

The results presented in Table 4 demonstrate the effect of spatial resolution in the formation of DEM and, consequently, in the spatial pattern of the LS factor, with reflections in the erosion prediction, for example, in the DEM with a resolution of 30 m, there was the lowest percentage of area in the “very low” class.

The occupation of the first three LS classes in more than 90% of the area was similar between the models LS2, LS3, and LS4, with similarity higher than 95% in the models from cartographic basis. In contrast, the LS1 model, which showed a difference of more than 10% in the first three classes, also being the one with the highest

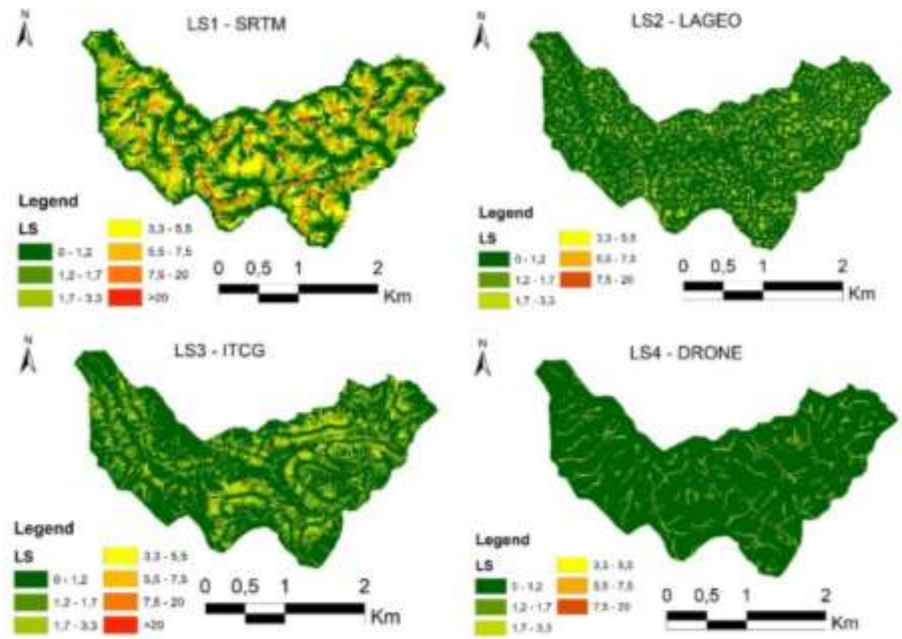

Figure 4. Spatial distribution of the LS factor.

percentage of area in the last three classes, even if not concentrated in the watershed.

About the topographic factor from the SRTM image, this map presented a maximum value of 38.10, with an average of 2.29, and among all generated maps, the one that presented the highest LS values. LS2 had a maximum value of 13.55 and an average of 0.86. LS3 map had 16.98 and 0.93 for the maximum and average value, respectively. About the map obtained via DRONE, the maximum value obtained was 21.02, and the average was 0.52. Figure 4 shows the spatial distribution of the LS factor in the watershed for each image studied.

This behavior can also be observed in Zhang et al. (2008), who when evaluating the effects of the resolution and the data source in the erosion modelling in two American forest watersheds, observed that both the resolution and the source of the models generated shapes and varied structures. This led to different lengths and slopes of reliefs and channels, producing different predictions of water erosion.

For Yang (2015), LS values calculated from different sources reveal that higher DEM resolutions produce more detailed LS maps; and lower quality resolutions tend to overestimate the value of this factor. These differences are more noticeable for a higher range of LS (LS>10), as shown in Figure 5.

About the LS4, this image obtained a better representation of the landscape, since a high resolution allows us to absorb and capture with greater precision the geomorphological aspects of the surface. In contrast, the LS2 and LS3 images showed a distribution between similar classes.

As shown by Aziz et al. (2012), depending on the input source, estimation methods, and procedures used to generate the DEM, the DEM may contain errors, which can affect the estimate not only of the LS factor but also of other parameters derived from the DEM. Thus, the choice of which resolution to use should consider which images are available and which one can represent all the characteristics of the watershed.

Zhao et al. (2010) show that the prediction of soil loss by RUSLE through high-resolution DEM is more appropriate since other resolutions may not represent the impact of deviation terraces in reducing soil loss.

These results reinforce the importance of adapting the mapping objectives according to the DEM, since changes in cell size cause differences between the slope maps, which can generate results that are either more conservative or more alarming from environmental management, affecting the adoption of conservationist policies in a given area.

According to Beskow et al. (2009), areas with LS greater than 10 are considered to be highly vulnerable to erosion, and therefore, erosion control mechanisms should be encouraged (Steinmetz et al., 2018), such as maintaining and improving vegetation cover and conservation practices of soil.

The results regarding the behavior of the LS factor as a function of spatial resolution, demonstrate that there is, effectively, a difference in the direction of flow and, consequently, in the topographic effect in the formation of water erosion, as was observed in the work of Panagos et al. (2015) who assessed water erosion in Europe.

Contrarily, only the topographic condition is not enough

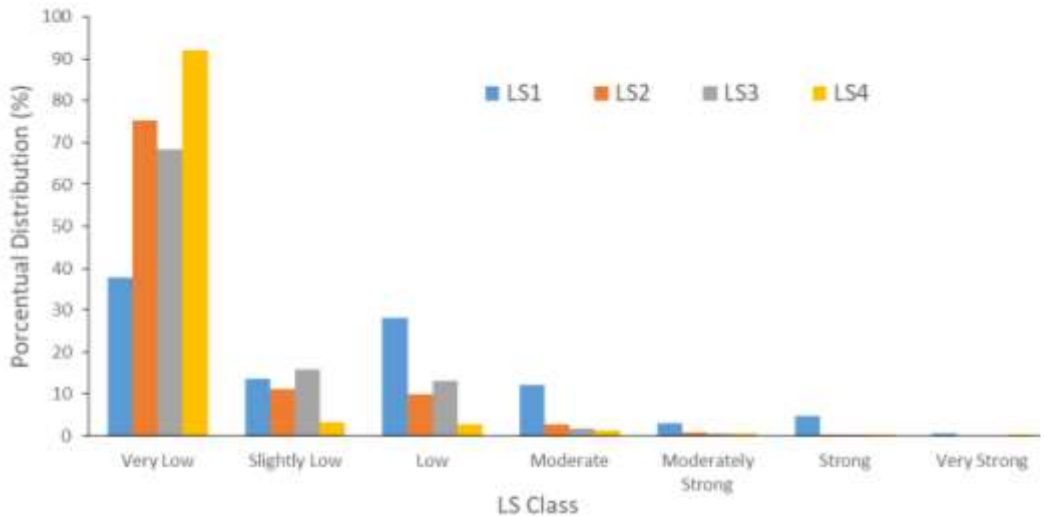

Figure 5. Percentage distribution of LS classes from spatial resolution.

to analyze the production of sediments in a watershed and, therefore, one must evaluate together with the other factors of RUSLE, mainly with the maps of land use and cover.

Given the spatial distribution of the LS factor, it is expected that maps obtained with the best resolutions, tend to produce more accurate DEM. Which results in less soil loss, as well as higher chances of success in monitoring areas degraded by water erosion, since most studies in this line in Brazil use SRTM 30 m data.

Once the other factors of RUSLE were consolidated, it was applied to estimate soil loss in different scenarios, since the process is dynamic and can range according to the use and occupation of the land. Thus, the distribution of erosion by climatic season is shown in Figure 6, for each of the resolutions, which allows identifying which periods require watershed management activities.

For the conditions presented, it is noted that with the decrease of the natural areas from autumn and with another small reduction in spring, areas susceptible to erosion processes increase, represented by the increase of fallow agriculture areas in autumn and spring. There was an increase in the area occupied with pasture between autumn and winter, with a reduction in the fallow area, which is traditionally characterized by the presence of exposed soil.

About the summer, the average potential erosion was higher on the map produced for the LS1 condition, with an average production of 45.08 t ha^{-1} year^{-1} of sediments. In contrast, the best condition obtained was from the DRONE image, with an average production of 10.64 t ha^{-1} year^{-1}. For the LS2 and LS3 images, the average potential sediment production was 18.75 and 19.78 t ha^{-1} year^{-1}, respectively.

About the periods, the highest estimated values in any scenario were in the areas close to the watershed outlet, where there is intense agricultural activity, and in the areas identified as a dirt road. According to Minella et al. (2007), these areas are the main sources of sediment production in a hydrographic watershed, and once the source of erosion has been identified, the implications for soil and water conservation can be assessed.

Less conservationist soil coverings can be replaced by coverings with less erosive potential, especially in places with higher LS values, as suggested by Caten et al. (2012). It is also possible to readjust the layout of rural roads, in addition to the build of rainwater catchment watersheds, reducing the kinetic energy of surface runoff and, consequently, the transport of suspended solids and the dragging of material to other areas of the watershed, as proposed by Casarin and Oliveria (2009).

About the period corresponding to autumn, there was a reduction in the area destined to native forest and conventional agriculture. This period is characterized by the soil preparation for the next harvest and the insertion of cattle in the watershed, justifying the increase in the fallow and pasture areas, respectively. Table 5 presents a summary of the main results found in the scenarios evaluated for water erosion.

The increase in the fallow area tends to increase sediment production. However, the observed increase occurred in flatter areas, decreasing the effect of the LS factor. In contrast, in the areas with higher LS, the pasture was inserted, potentially reducing the effect of erosion. In this period, an average value of 43.07 t ha^{-1} year^{-1} was observed for LS1, 19.41 t ha^{-1} year^{-1} for LS2, 21.20 t ha^{-1} year^{-1} for LS3, and 9.92 t ha^{-1} year^{-1} for LS4. For winter, the average sediment potential decreased in all scenarios, with LS1 presenting 32.45 t ha^{-1} year^{-1}; LS2 with 13.46 t ha^{-1} year^{-1}; LS3 with an average value of 13.37 t ha^{-1} year^{-1} and LS4 presented 7.24 t ha^{-1} year^{-1}.

One of the reasons that may explain this reduction

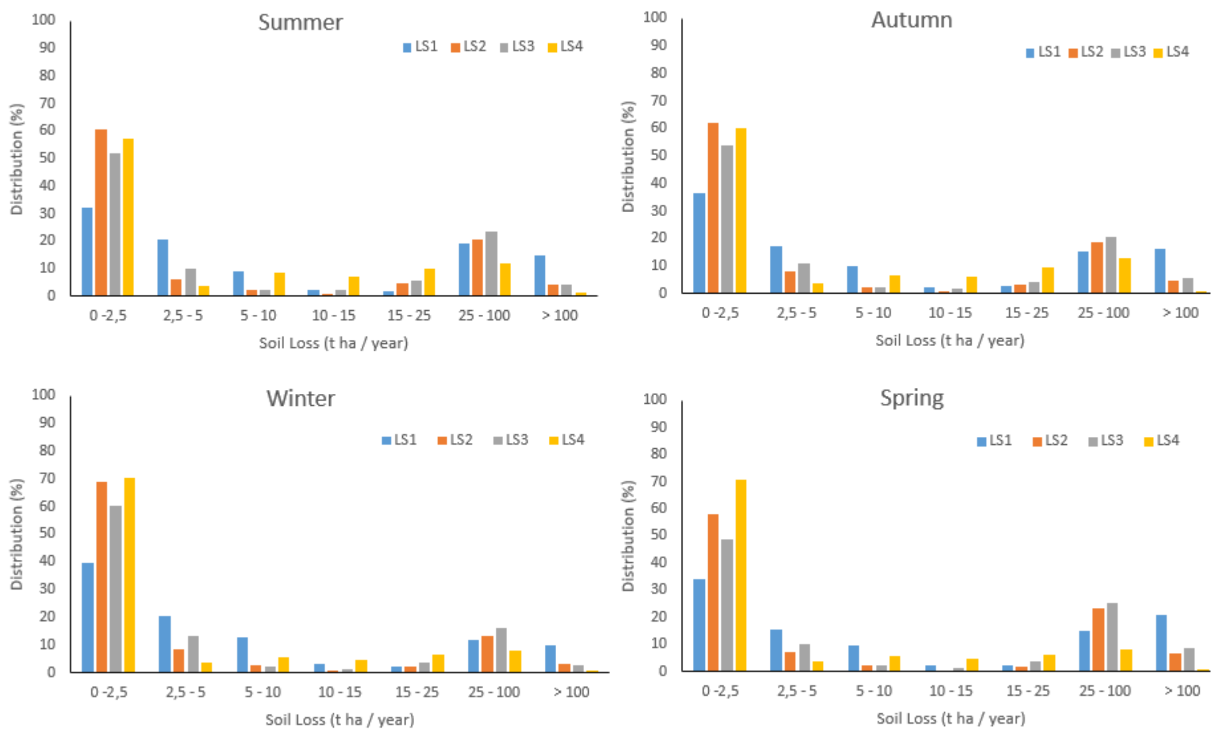

Figure 6. Distribution of the potential erosion in the evaluated scenarios.

Table 5. Estimated soil loss values, according to seasonality.

Season		LS1	LS2	LS3	LS4
	Maximum soil loss (t ha^{-1} year^{-1})	2,411.57	612.28	1073.52	838.50
Summer	Average soil loss (t ha^{-1} year^{-1})	45.08	18.75	19.78	10.64
	Standard deviation (t ha^{-1} year^{-1})	112.67	41.64	40.12	28.32
	Maximum soil loss (t ha^{-1} year^{-1})	1,134.10	733.58	751.23	463.29
Autumn	Average soil loss (t ha^{-1} year^{-1})	43.07	19.41	22.10	9.92
	Standard deviation (t ha^{-1} year^{-1})	88.62	46.53	45.95	22.17
	Maximum soil loss (t ha^{-1} year^{-1})	2,411.57	681.08	652.24	936.81
Winter	Average soil loss (t ha^{-1} year^{-1})	32.45	13.46	13.37	7.24
	Standard deviation (t ha^{-1} year^{-1})	112.21	38.37	32.53	26.24
	Maximum soil loss (t ha^{-1} year^{-1})	1,911.74	733.58	1073.52	597.07
Spring	Average soil loss (t ha^{-1} year^{-1})	53.77	25.31	27.66	13.04
	Standard deviation (t ha^{-1} year^{-1})	106.95	52.44	51.96	27.12

concerning the previous period is the decrease of the fallow area (C = 0.5) and an increase of the pasture area.

For the spring, there was an increase in the average values of potential water erosion, with LS1 presenting 53.77 t ha^{-1} year^{-1}; LS2 had an estimated average production of 25.31 t ha^{-1} year^{-1}; LS3 with approximately 27.66 t ha^{-1} year^{-1}, and LS4 producing 13.04 t ha^{-1} year^{-1}. In the winter, most of the areas were occupied with fallow, with a decrease in pasture areas and native forests.

Traditionally, both autumn and winter period is characterized by the low amount of rainfall events in Brazil, and therefore less sediment transport when compared to periods of convective rain (spring/summer). This behavior can explain the low values of avarege soil loss found in those periods associated to changes in land use and land management that may increase soil erosion, but without significant precipitation, soil losses tend to be less.

The importance of plant cover in controlling water erosion is widely accepted. In the short term, vegetation influences erosion mainly by intercepting rainfall and protecting the soil surface against the impact of rainfall drops, and by intercepting runoff. In the long term, vegetation influences the fluxes of water and sediments by increasing the soil-aggregate stability and cohesion as well as by improving water infiltration (Zuazo and Pleguezuelo, 2008).

According to Beutler et al. (2003), in the spring/summer period, on average, soil losses are twice as high as in the autumn/winter period. Although the values found in this study are not of this magnitude, the estimated losses follow this pattern of behavior in the analyzed periods.

In the case of modeling soil erosion, a higher resolution provides better and more accurate results and will reduce uncertainty, while lower resolution provides generalized results (Mondal et al., 2017).

The analysis of temporal changes occurred serves as a subsidy for the implementation of more efficient erosion control practices, especially about soil management. Mainly because most studies of the potential for water erosion using RUSLE in Brazil, do not consider seasonality and, many times, have overestimated values.

It is observed that natural resources are under increasing pressure due to climate change, population growth, and competing demands for the use of the resource. Which demands not only more effective governance but also a significant improvement in accessibility, especially in the use of information about these possible impacts at the watershed scale, as shown by Vörösmarty et al. (2010), Pahl-Wostl (2007), Kirchhoff et al. (2013), among others.

According to Rodrigues et al. (2017), this type of analysis presents itself as an effective tool to estimate the vulnerability to erosion, since it allows the identification of the most susceptible areas and subsidizes ecological services aimed at sustainability, a key aspect in the development and formalization of public policies for watershed management

Therefore, the use of high-resolution images is an alternative that goes in the direction of this process of development and improvement of environmental policies. Which allows access to more accurate information and, consequently, in reducing costs, be it in the dimensioning of rural roads, in construction of terracing systems or, in the reforestation of the most critical areas for water erosion within the watershed.

Conclusion

Soil loss was estimated to the entire study area, ranging from 0 to more than 2000 t ha^{-1} $year^{-1}$. The most susceptible areas were found in areas with the highest LS values and those classified as dirty roads, therefore reinforcing the need for conservation practices to promote sustainable agricultural practices on more steep terrain. The results found in this study stand out as one of the pioneer studies of this nature for Paraná state, thus playing an essential role in the soil and water resources management of the region. Future studies should focus on direct field measurements of soil loss in this watershed to validate the results estimated according to the RUSLE.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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