

MAPPING SOIL EROSION RISK IN RONDÔNIA, BRAZILIAN AMAZONIA: USING RUSLE, REMOTE SENSING AND GIS

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ABSTRACT

This article discusses research in which the authors applied the Revised Universal Soil Loss Equation (RUSLE), remote sensing, and geographical information system (GIS) to the mapping of soil erosion risk in Brazilian Amazonia. Soil map and soil survey data were used to develop the soil erodibility factor (K), and a digital elevation model image was used to generate the topographic factor (LS). The cover-management factor (C) was developed based on vegetation, shade, and soil fraction images derived from spectral mixture analysis of a Landsat Enhanced Thematic Mapper Plus image. Assuming the same climatic conditions and no support practice in the study area, the rainfall–runoff erosivity (R) and the support practice (P) factors were not used. The majority of the study area has K values of less than 0.2, LS values of less than 2.5, and C values of less than 0.25. A soil erosion risk map with five classes (very low, low, medium, medium-high, and high) was produced based on the simplified RUSLE within the GIS environment, and was linked to land use and land cover (LULC) image to explore relationships between soil erosion risk and LULC distribution. The results indicate that most successional and mature forests are in very low and low erosion risk areas, while agroforestry and pasture are usually associated with medium to high risk areas. This research implies that remote sensing and GIS provide promising tools for evaluating and mapping soil erosion risk in Amazonia. Copyright © 2004 John Wiley & Sons, Ltd.

KEY WORDS: soil erosion risk; RUSLE; remote sensing; GIS; Brazilian Amazonia

INTRODUCTION

The adverse influences of widespread soil erosion on soil degradation, agricultural production, water quality, hydrological systems, and environments, have long been recognized as severe problems for human sustainability (Lal, 1998). However, estimation of soil erosion loss is often difficult due to the complex interplay of many factors, such as climate, land cover, soil, topography, and human activities. In addition to the biophysical parameters, social, economic, and political components also influence soil erosion (Ananda and Herath, 2003). Accurate and timely estimation of soil erosion loss or evaluation of soil erosion risk has become an urgent task.

Scientists have been involved in soil erosion research for a long time, and many models for soil erosion loss estimation have been developed (Wischmeier and Smith, 1978; Nearing *et al.*, 1989; Adinarayana *et al.*, 1999; D'Ambrosio *et al.*, 2001; Veihe *et al.*, 2001; Shen *et al.*, 2003). Fullen (2003) summarized some keynote papers about soil erosion in northern Europe, and Lal (2001) highlighted major empirical models for predicting soil erosion loss. In practice, the Universal Soil Loss Equation (USLE) and later the Revised Universal Soil Loss

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Equation (RUSLE) has been the most widely used model in predicting soil erosion loss. The USLE was originally developed for soil erosion estimation in croplands on gently sloping topography (Wischmeier and Smith, 1978). The RUSLE has broadened its application to different situations, including forest, rangeland, and disturbed areas (Renard *et al.*, 1997). Traditionally, these models were used for local conservation planning at an individual property level. The factors used in these models were usually estimated or calculated from field measurements. The methods of quantifying soil loss based on erosion plots possess many limitations in terms of cost, representativeness, and reliability of the resulting data. They cannot provide spatial distribution of soil erosion loss due to the constraint of limited samples in complex environments. So, mapping soil erosion in large areas is often very difficult using these traditional methods.

The use of remote sensing and geographical information system (GIS) techniques makes soil erosion estimation and its spatial distribution feasible with reasonable costs and better accuracy in larger areas (Millward and Mersey, 1999; Wang *et al.*, 2003). For example, a combination of remote sensing, GIS, and RUSLE provides the potential to estimate soil erosion loss on a cell-by-cell basis (Millward and Mersey, 1999). Boggs *et al.* (2001) assessed soil erosion risk based on a simplified version of RUSLE using digital elevation model (DEM) data and land-units maps. Bartsch *et al.* (2002) used GIS techniques to interpolate RUSLE parameters for sample plots to determine the soil erosion risk at Camp Williams, Utah. Wilson and Lorang (2000) reviewed the applications of GIS in estimating soil erosion, discussed the difficulty and limitations of previous research and identified that GIS provided tremendous potential for improving soil erosion estimation. Wang *et al.* (2003) used a sample ground dataset, Thematic Mapper (TM) images, and DEM data to predict soil erosion loss through geostatistical methods (i.e., collocated cokriging and a joint sequential cosimulation model). They showed that such methods provided significantly better results than using traditional methods. In general, remote-sensing data were primarily used to develop the cover-management factor image through land-cover classifications (Millward and Mersey, 1999; Reusing *et al.*, 2000; Ma *et al.*, 2003), while GIS tools were used for derivation of the topographic factor from DEM data, data interpolation of sample plots, and calculation of soil erosion loss (Cerri *et al.*, 2001; Bartsch *et al.*, 2002; Wang *et al.*, 2003).

In many situations, land managers and policy makers are more interested in the spatial distribution of soil erosion risk than in absolute values of soil erosion loss. Different approaches have been used to assess the soil erosion risk, including empirical erosion models (Boggs *et al.*, 2001; Cerri *et al.*, 2001; Bartsch *et al.*, 2002), a ranking method based on selected indicators such as percentage of bare ground, aggregate stability, organic carbon, percentage clay, and bulk density (Shakesby *et al.*, 2002), and qualitative erosion risk mapping based on the combination of five factors (geology, soil, relief, climate, and vegetation) (Vrieling *et al.*, 2002).

Brazilian Amazonia has experienced high deforestation rates since the 1970s, with large areas of mature forest being converted to patches of different successional stages, agricultural lands, and pastures (Batistella *et al.*, 2003). The deforestation has been recognized as a major cause of soil degradation through soil erosion and the changes in important climate and ecosystem components (Thiam, 2003). However, the evaluation of soil erosion risk within Brazilian Amazonia has not attracted sufficient scientific attention. This article explores this topic using a simplified RUSLE based on the integration of remote sensing and GIS in the moist tropical region of the Brazilian Amazonia and examines the relationships between land use and land cover (LULC), and soil erosion risks.

BRIEF DESCRIPTION OF THE RUSLE

The RUSLE represents how climate, soil, topography, and land use affect rill and interrill soil erosion caused by raindrop impact and surface runoff (Renard *et al.*, 1997). It has been extensively used to estimate soil erosion loss, to assess soil erosion risk, and to guide development and conservation plans in order to control erosion under different land-cover conditions, such as croplands, rangelands, and disturbed forest lands (Millward and Mersey, 1999; Boggs *et al.*, 2001; Mati and Veihe, 2001; Angima *et al.*, 2003). The RUSLE is expressed as:

$$A = R K L S C P, \quad (1)$$

Table I. Summary of main methods for developing RUSLE parameters

	Methods	References
<i>R</i>	Using erosion index values for all rainfall storms in one year	Wischmeier and Smith, 1978
	Using average monthly precipitation and average annual precipitation	Renard and Fremund, 1994
	Using a regression model based on measured annual precipitation	Millward and Mersey, 1999
	Using a regression model of the <i>R</i> factor with average annual precipitation and elevation data	Mikhailova <i>et al.</i> , 1997
	Using geostatistical methods such as kriging estimators	Goovaerts, 1999
	Using simulation techniques such as sequential Gaussian simulation	Wang <i>et al.</i> , 2002a
<i>K</i>	Using the experimental models based on soil properties (composition of sand–silt–clay percentages, organic matter, structure, and permeability of the soil profile)	Wischmeier and Smith, 1978
	Using regression equation based on soil properties (percentages of unstable aggregates, silt, sand, and base saturation)	Angima <i>et al.</i> , 2003
	Using the published <i>K</i> values by USDA-NRCS	Soil Survey Staff, 1997
	Based on size of soil particulates	Romken, 1983
	Using geostatistical methods such as joint sequential simulation and sequential Gaussian simulation	Parysow <i>et al.</i> , 2003, Wang <i>et al.</i> , 2001
<i>LS</i>	Estimated from actual field measurements of length and steepness	Wischmeier and Smith, 1978
	Calculated from DEM data with various approaches	Hickey, 2000; Van Remortel <i>et al.</i> , 2001
<i>C</i>	Using individual soil-loss ratio values and the factor of rainfall and runoff erosivity	Renard <i>et al.</i> , 1997
	Combination of individual <i>C</i> factor from empirical models and remote-sensing classification image	Millward and Mersey, 1999
	From supervised land-cover classification of multispectral MOMS-02/D2 data	Reusing <i>et al.</i> , 2000
	Geostatistical techniques	Wang <i>et al.</i> , 2002b
	Greenness index	Ma <i>et al.</i> , 2003
<i>P</i>	Experimental data	Renard <i>et al.</i> , 1997

where *A* is the average annual soil loss in tons per acre; *R* is the rainfall-runoff erosivity factor; *K* is the soil erodibility factor; *L* is the slope length factor; *S* is the slope steepness factor; *C* is the cover-management factor; and *P* is the support practice factor. Table I summarizes the main methods for estimating these factors. Previous literature has described these methods extensively.

STUDY AREA

Rondônia has experienced high deforestation rates during the past two decades (INPE, 2002). Following the national strategy of regional occupation and development, colonization projects initiated by the Brazilian Government in the 1970s played a major role in this process (Moran, 1981). The colonists transformed the forested landscape into a patchwork of cultivated crops, pastures, successional vegetation, and remnant forests (Batistella, 2001).

The study area is located at Machadinho d'Oeste, in northeastern Rondônia (Figure 1). The climate in this study area is classified as equatorial hot and humid with tropical transition. A well-defined dry season lasts from June to August, and the annual average precipitation is 2016 mm (Rondônia, 1998). The annual average temperature is 25.5°C, and monthly averages for air moisture range from 80 to 85 per cent. The terrain is undulating, ranging from 100 to 400 m above sea-level. Several soil types were identified, mainly alfisols, oxisols, ultisols, alluvial soils, and other less spatially represented associations (Bognola and Soares, 1999; Valladares *et al.*, 2003).

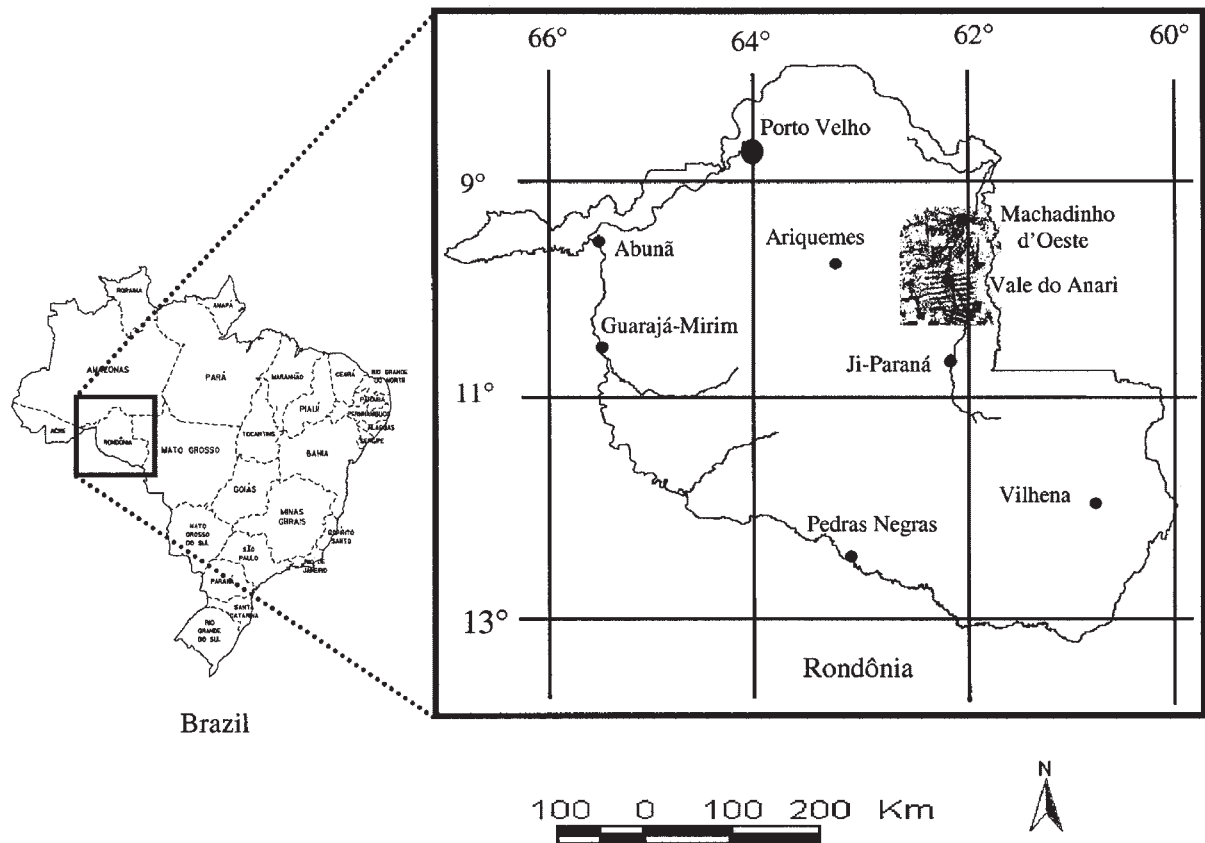


Figure 1. Location of the study area in the State of Rondônia, Brazilian Amazonia.

DATA PREPARATION

Landsat 7 ETM+ (path/row: 231/67) was acquired on 27 June 2002. The image was converted to apparent reflectance through an image-based calibration method using the gain, offset, and sun elevation angle (Markam and Barker, 1987). This image was also geometrically rectified using control points collected from topographic maps so that the image can be accurately linked to ground reference data and other ancillary data, such as soil type map and DEM data. The nearest-neighbor resampling technique was used and a root-mean-square error with less than 0.5 pixels was obtained during the image geometric rectification.

Field data collection was conducted in August 2002. Different LULC types, such as mature forest, successional forest, agroforestry (mainly coffee plantations), and pasture, were identified and their coordinates were recorded with a GPS device. These data were used as training samples for supervised classification of ETM+ data. About 10 to 15 sample plots for each class were selected. Maximum likelihood classifier (MLC) was used to classify the ETM+ data into six LULC classes: mature forest; successional forest; agroforestry; pasture; urban; and water. A majority filter with a 3×3 window size was used to remove the 'salt and pepper' noise in the classified image. Accuracy assessment using field data collected in August 2003 indicated an overall accuracy of approximately 90 per cent. Figure 2 shows the LULC distribution within the study area. A detailed description of LULC classification using MLC can be found in Lu *et al.* (2004).

The soil map was generated in 2003 based on interpretation of landforms and pedoforms within the landscape using Landsat TM data and aerial photographs, corroborated by soil field surveys. The representative soil profile samples were collected, described, and characterized according to the Soil Survey Manual (Soil Survey Staff,

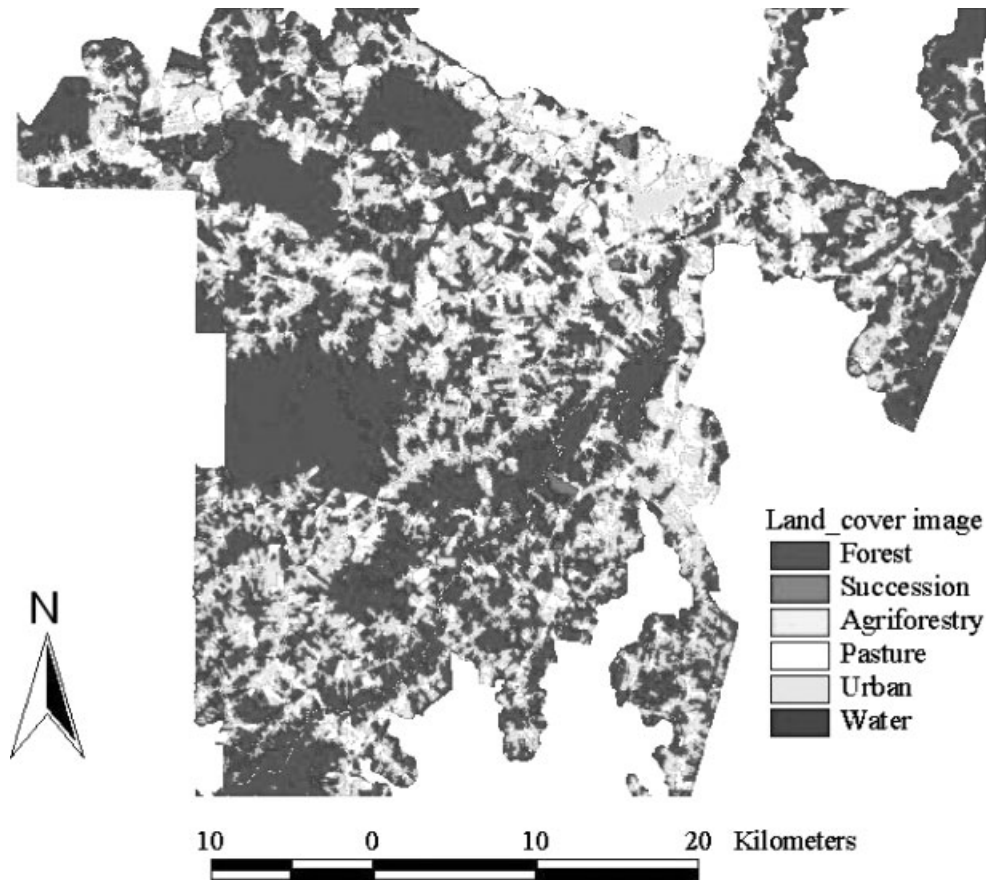


Figure 2. Land-use and land-cover classification for the study area based on ETM+ data.

1993), Lemos and Santos (1996), and Embrapa (1999). The soil types were classified according to Soil Taxonomy (Soil Survey Staff, 1998, 1999). A more detailed description of the soils in this study area can be found in Valladares *et al.* (2003) and in Embrapa (1999). Figure 3 illustrates the distribution of soil types in this study area.

Fieldwork for collecting soil sample plots was conducted in September 2002. A total of 22 samples were collected in representative points of the study area based on relief, soil, and land-cover (Valladares *et al.*, 2003). During fieldwork, the position on the relief, morphologic description, color, structure, consistency, texture, and other parameters, were recorded. In the lab, soil pH, CaCl_2 , content of Ca, Mg, K, Na, H, Al, sum of bases, cation exchange capacity, P, organic carbon, clay, silt, and sand were analyzed. The sampling strategy was based on the representativeness of the soil's orders and suborders occurring in the study area (Soil Survey Division Staff, 1993; Lemos and Santos, 1996; Embrapa, 1999).

Contour lines, rivers, and typical points were digitized based on 1:100 000 topographic maps (UTM, South American, Zone 20), then a 30-meter spatial resolution DEM was generated using ArcGIS. Figures 4 and 5 illustrate the elevation and slope distribution for the study area. Most elevations are between 100 and 300 m and are associated with gentle slopes (less than 5 degrees).

EVALUATION OF THE SOIL EROSION RISK

Six parameters are required for the soil erosion estimation, as described previously. Because this study focuses on the evaluation of soil erosion risk, instead of estimation of actual soil erosion loss, the *R* and *P* factors were not

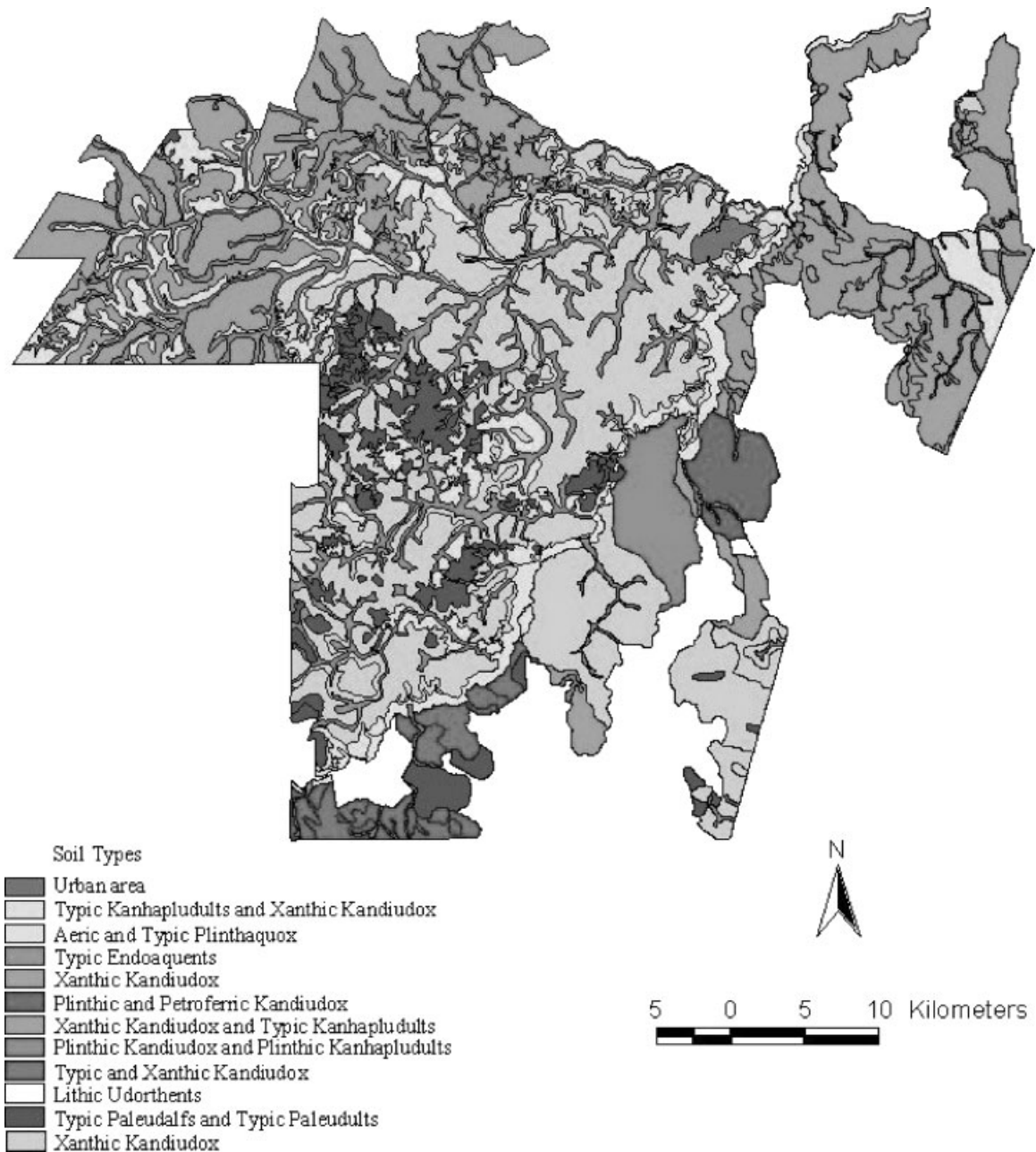


Figure 3. Spatial distribution of soil types within the study area.

used, assuming that same climatic conditions and no support practices existed within the study area. So the soil erosion risk (SER) was developed based on K , LS , and C factors in a simplified equation: $SER = K LS C$.

Development of the K Factor Image

The K factor is related to the integrated effects of rainfall, runoff, and infiltration on soil loss, accounting for the influences of soil properties on soil loss during storm events on upland areas (Renard *et al.*, 1997). It is often

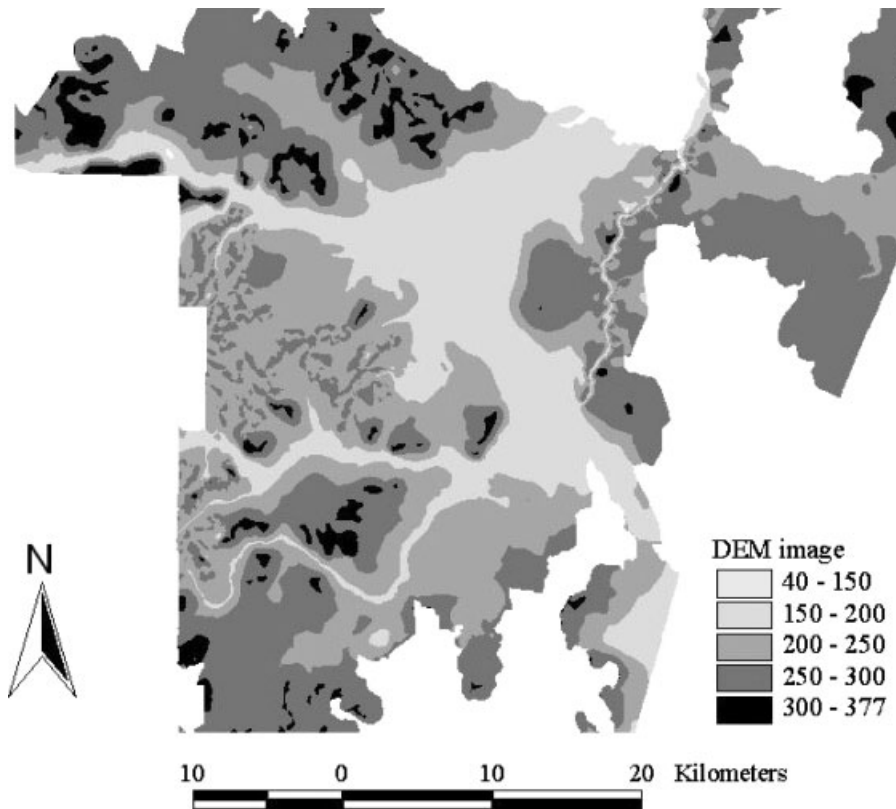


Figure 4. Grey-scale image illustrating elevation classes within the study area.

estimated through experimental equations (e.g., Equation 2) or corresponding nomographs (Wischmeier and Smith, 1978).

$$K = 2.1 \times 10^{-6} \times M^{1.14} \times (12 - OM) + 0.0325 \times (P - 2) + 0.025 \times (S - 3), \quad (2)$$

where $M = (\%silt + \%very_fine_sand)(100 - \%clay)$; OM = percentage of organic matter; P = permeability class; and S = structure class.

The K value for each sample plot was calculated, then each soil type was associated with a K value assuming that the same soil type has the same K value throughout the study area. Figure 6 illustrates the K factor distribution. It indicates that most of the study area has a K value of less than 0.2.

Development of the LS Factor Image

The LS factor accounts for the effect of topography on erosion in RUSLE. The slope length factor (L) represents the effect of slope length on erosion, and the slope steepness factor (S) reflects the influence of slope gradient on erosion. The common equation used for calculating LS is an empirical equation (see Equation 3) provided by the USDA *Agriculture Handbook* (Wischmeier and Smith, 1978).

$$LS = \left(\frac{\lambda}{22.13} \right)^n (65.41 \sin^2 \theta + 4.56 \sin \theta + 0.065), \quad (3)$$

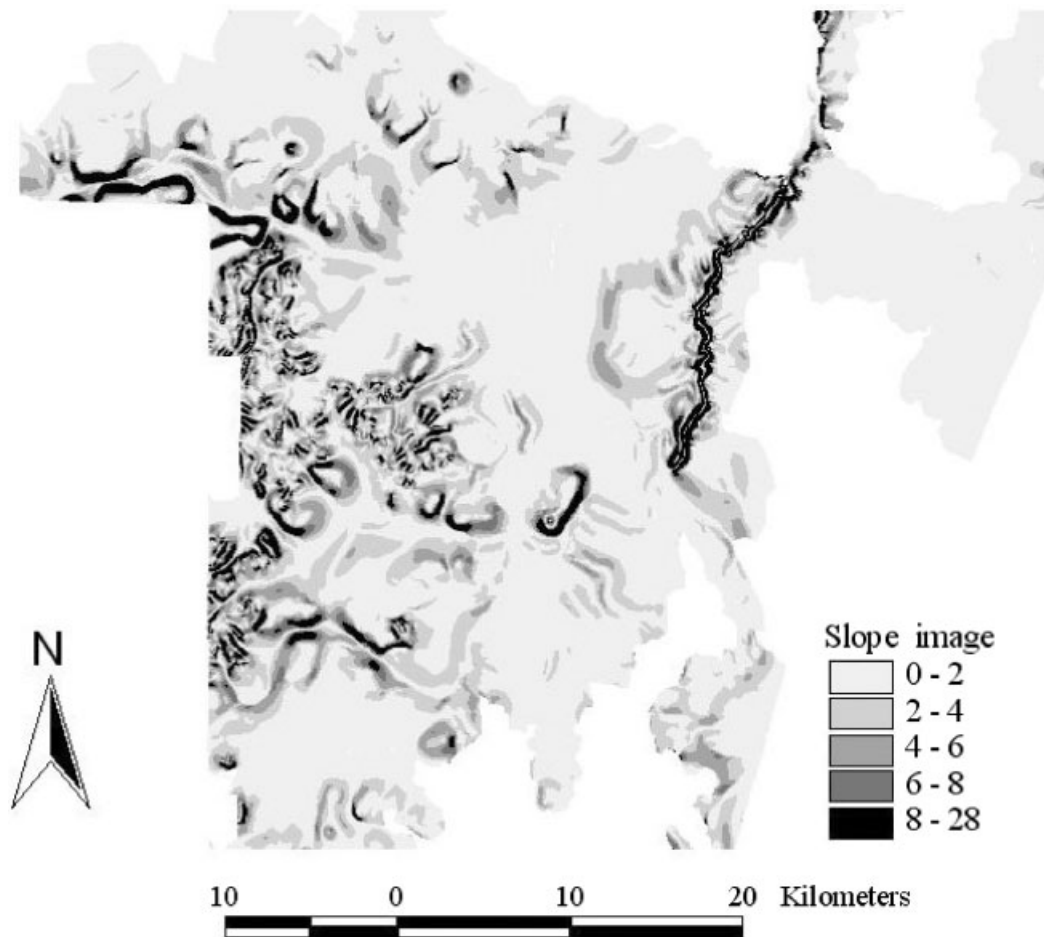


Figure 5. Grey-scale image illustrating slope classes within the study area.

where λ is the slope length in meters; θ is the angle of slope in degrees; and n is a constant dependent on the value of the slope gradient: 0.5 if the slope angle is greater than 2.86 degrees, 0.4 on slopes of 1.72 to 2.85 degrees, 0.3 on slopes of 0.57 to 1.72 degrees, and 0.2 on slopes less than 0.57 degrees.

The RUSLE-based ArcInfo Arc Macro Language (AML) program for computing the *LS* factor was developed using the raster grid cumulation and maximum downhill slope methods (Hickey, 2000; Van Remortel *et al.*, 2001) and is available at the following website: www.cwu.edu/~rhickey/slope/slope.html. Figure 7 illustrates the *LS* factor distribution. It indicates that the majority of the study area has *LS* values of less than 2.5. Some specific areas with steep slopes, such as along the river, have *LS* values of greater than 2.5.

Development of the C Factor Image

The *C* factor reflects the effects of cropping and management practices on soil erosion rates in agricultural lands and the effects of vegetation canopy and ground covers on reducing the soil erosion in forested regions (Renard *et al.*, 1997). Usually, the *C* factor is derived using empirical equations based on the measurements of many variables related to ground covers collected in the sample plots. The *C* factor values at non-sampled locations were estimated through spatial interpolation techniques. This method is often time-consuming and computer intensive. It only provides point values with limited locations. The interpolation results based on the *C* factor point values

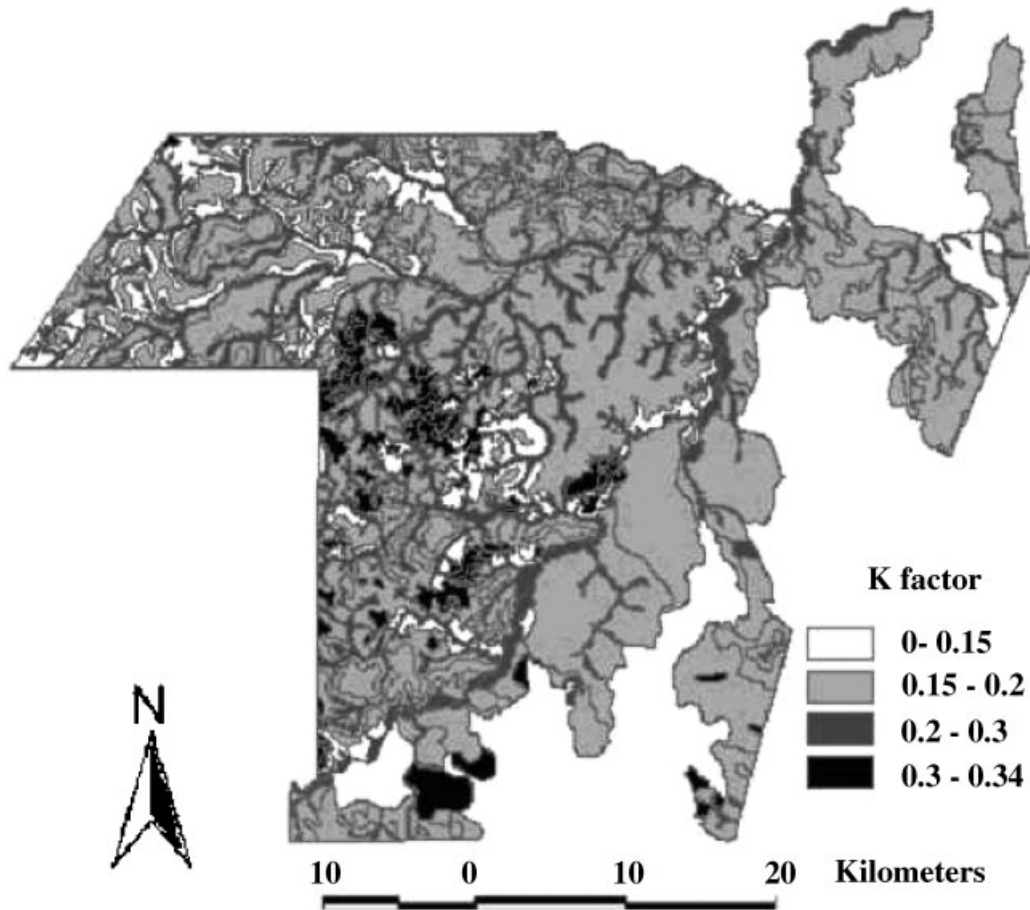


Figure 6. The soil erodibility factor developed from soil sample plots data and soil map.

could be poor due to the limited number of sample plots in complex environments (Wang *et al.*, 2002b). Therefore, remotely sensed data have been used to estimate the C factor distribution based on land-cover classification results (Millward and Mersey, 1999; Reusing *et al.*, 2000), assuming that the same land covers have the same C factor values. The result greatly depends on: (1) the details of land-cover classes and classification accuracy; and (2) the determination of a suitable C factor value for each class. However, the same land-cover class may have different C factors due to variations in vegetation density.

In this study, the C factor was estimated (see Equation 4) based on the fraction images from spectral mixture analysis (SMA) of Landsat ETM+ image, assuming that abundant vegetation cover associated with a complex stand structure results in less soil erosion loss, while more soil fraction associated with less vegetation cover results in higher soil erosion loss.

$$C = \frac{f_{\text{soil}}}{1 + f_{\text{gv}} + f_{\text{shade}} + f_{\text{gv}} \times f_{\text{shade}}}, \quad (4)$$

where f_{soil} , f_{gv} , and f_{shade} are the three fraction values of soil, green vegetation, and shade endmembers. The values of f_{soil} , f_{gv} , and f_{shade} parameters range from 0 to 1 and their sum equals 1. A detailed description of SMA can be

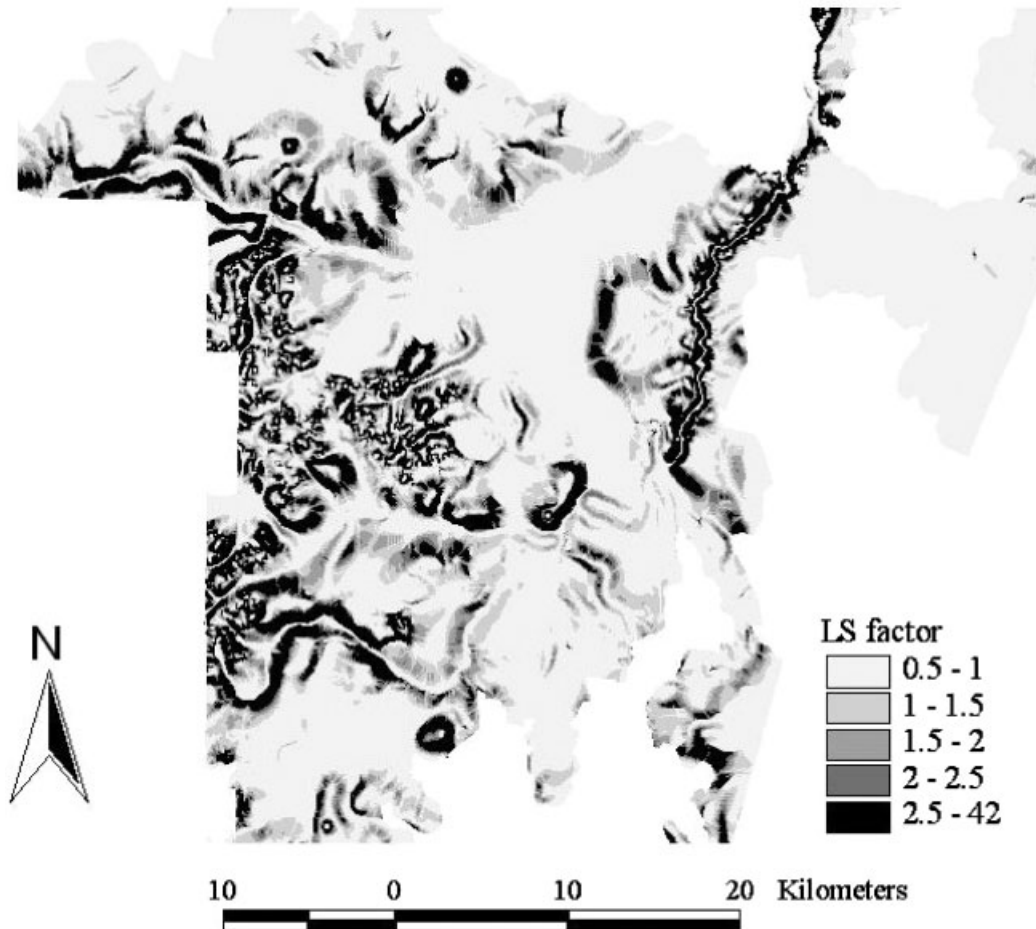


Figure 7. The topographic factor developed from the DEM data.

found in Lu *et al.* (2003). Figure 8 illustrates the *C* factor distribution. The majority of the study area has *C* values of less than 0.25. Very few areas have *C* values greater than 0.5.

Development of the Soil Erosion Risk Image

After the *K*, *LS*, and *C* factor images were developed, they were overlaid using GIS tools to generate the SER image. Five risk levels, i.e., very low, low, medium, medium-high, and high, were identified and mapped (Figure 9). The majority of the study area has very low and low risk levels. Very few areas fall in medium-high and high risk levels.

Relating the LULC Image and the SER Image

A linkage between the LULC and the SER images is valuable for understanding how different LULC classes affect soil erosion. The LULC classes were recorded as 1, 2, 3, 4, and 5, corresponding to forest, successional forest, agroforestry, pasture, and others (urban and water), respectively. The SER image was also recorded as 1, 2, 3, 4 and 5 corresponding to very low, low, medium, medium-high, and high levels, respectively. These two images were compared pixel by pixel to generate a table indicating the relationship of LULC and SER classes. Table II provides the percentage of SER with LULC classes. It indicates that mature forest, most successional forests and

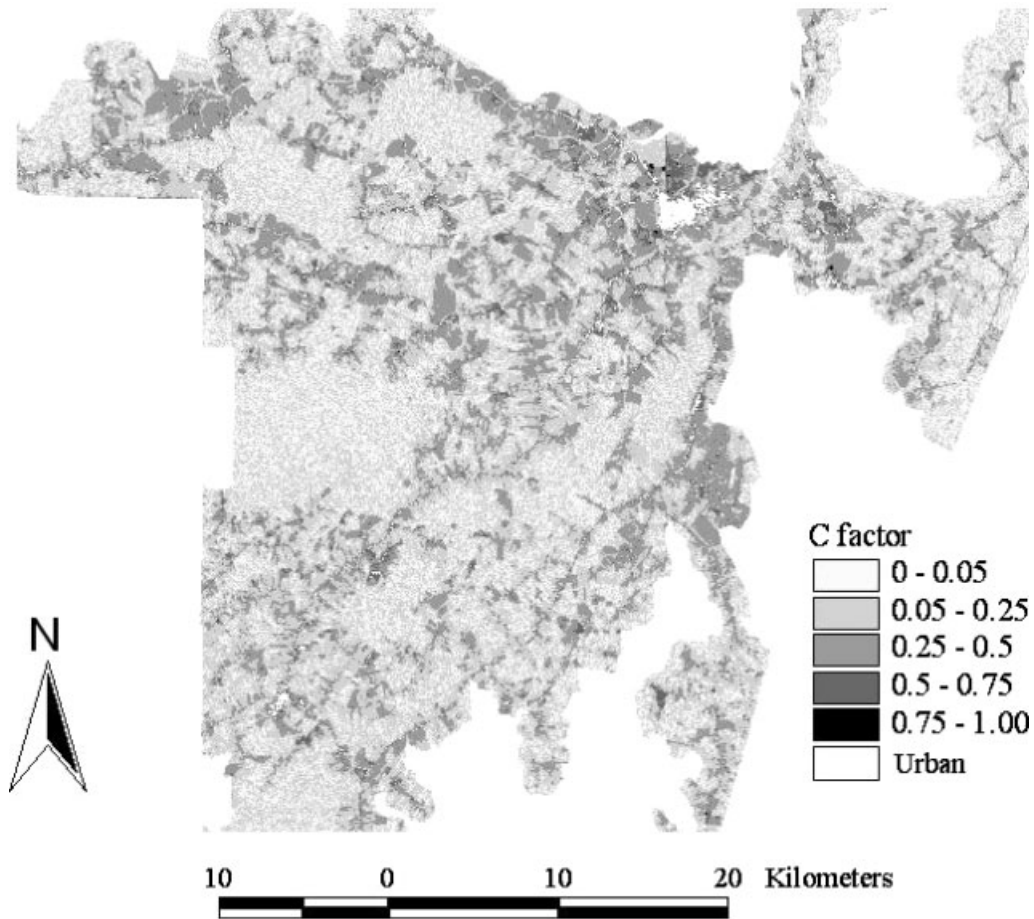


Figure 8. The cover-management factor developed using vegetation, shade, and soil fractions of ETM+ data.

agroforestry have very low or low erosion risks, but some of the pasture and agroforestry areas with limited ground cover have medium-high or high erosion risks. Table II also shows that very few areas of mature forest had medium or medium-high erosion risk. These pixels were located at the juncture of mature forests and other land covers due to the misregistration between ETM+, DEM, and soil data.

DISCUSSION AND CONCLUSIONS

RUSLE was originally developed for the USA, but also has been proven valuable for estimation of soil erosion loss in other regions of the world (Millward and Mersey, 1999; Reusing *et al.*, 2000; Angima *et al.*, 2003, Ma *et al.*, 2003). In general, RUSLE is used for estimating average annual soil erosion loss based on sample plot data. The use of remote sensing and GIS allows us to map the spatial distribution of soil erosion risk. However, because remotely sensed data capture the surface characteristics at the time of the image acquisition, caution must be taken when developing the *C* factor image. Calibration of the results using reference data may be necessary if it is used for estimation of absolute soil erosion loss. Also, the use of multitemporal remotely sensed data may be necessary to generate an average *C* factor image.

Six parameters, derived from different data sources such as DEM, soil, climate, and remotely sensed data, are used in the RUSLE. The different data sources may have different data formats, projections, data quality, and

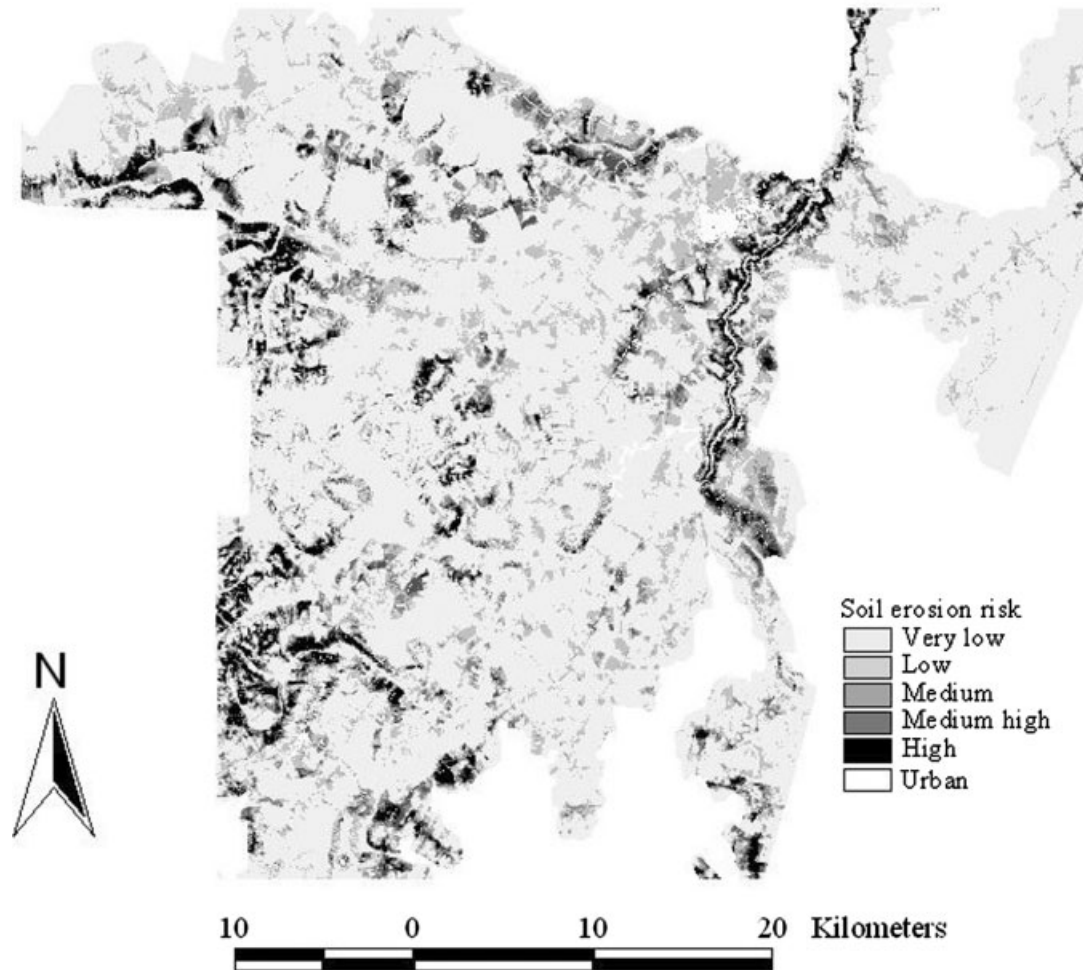


Figure 9. Erosion risk image illustrating the soil erosion conditions within the study area.

Table II. Assessment of soil erosion risk and associated land-cover distribution

LULC type	Soil erosion risk					Total (%)
	Very low (%)	Low (%)	Medium (%)	Medium-high (%)	High (%)	
Forest	43.30	2.53	0.87	0.52	0.31	47.53
Succession	9.05	0.94	0.31	0.19	0.15	10.64
Agroforestry	15.22	6.18	2.16	1.33	1.38	26.27
Pasture	2.54	7.09	2.51	1.73	1.67	15.54
Total (%)	70.11	16.74	5.85	3.77	3.51	

spatial resolution. The use of GIS provides the tools to manage and analyze these data. However, the evaluation of these data is necessary before they are used. The uncertainties regarding data sources may introduce larger uncertainties in soil erosion estimates. Great attention should be paid to the evaluation and preprocessing of data sources, such as data interpolation, conversion, and registration.

Estimation of soil erosion loss in a large area is often difficult, as well as its validation. Although this paper focuses on the evaluation of soil erosion risk, validation using reference data is also valuable. For example, if reference data are available, the classification of soil erosion risk and the identification of thresholds for each risk level will be more appropriate.

In summary, this study provides an approach for the evaluation of soil erosion risk in Brazilian Amazonia based on a combination of RUSLE, remote sensing, and GIS. This is an effective way to map the spatial distribution of soil erosion risks in a large area. The methods and results described in this article are valuable for understanding the relationship between soil erosion risk and LULC classes and are useful for managing and planning land use that will avoid land degradation. For Brazilian Amazonia, such topics are very important due to current activities involving forest conversion to other land covers.

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