UNIVERSIDADE FEDERAL DE MATO GROSSO DO SUL
FACULDADE DE ENGENHARIAS, ARQUITETURA E URBANISMO E GEOGRAFIA
PROGRAMA DE PÓS-GRADUAÇÃO EM TECNOLOGIAS AMBIENTAIS

RAQUEL DE FARIA GODOI

High-resolution soil erodibility map of Brazil

Campo Grande
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Dissertação apresentada para obtenção do grau de Mestre pelo Programa de Pós-Graduação em Tecnologias Ambientais da Faculdade de Engenharias, Arquitetura e Urbanismo e Geografia da Universidade Federal de Mato Grosso do Sul.

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ABSTRACT

Godoi, R. F., Rodrigues, D. B. B., Borrelli, P., Oliveira, P. T. S. (2021). **High-resolution soil erodibility map of Brazil**. *Science of The Total Environment, 781, 146673.* https://doi.org/10.1016/j.scitotenv.2021.146673

Large-scale soil erosion modeling has a crucial role in the understanding and planning of soil and water conservation strategies. The lack of spatial data on soil characteristics required to compute the soil erodibility (K-factor) has been one of the greatest obstacles in Brazil. The K-factor is a complex property that expresses the susceptibility of soil to erode according to its inherent characteristics. This factor is a key input parameter for the most widely applied soil erosion models: the Universal Soil Loss Equation (USLE) and the Revised USLE (RUSLE). Here, we computed a high-resolution (250 m cell size) spatially explicit soil erodibility map across Brazil. To compute the K-factor, we applied the equations originally proposed in the USLE nomograph (*USDA-Agriculture Handbook*, **537**, 1978) and EPIC (*Journal of Soil and Water Conservation*, **38**, 381–383, 1983), using the following soil properties, organic matter content, soil texture, soil structure, and permeability. To qualitatively evaluate our new K-factor map, its values were compared against standard K-factor values obtained from experimental plots across Brazil. We find that the USLE nomograph leads to a more precise estimation of the K-factor in Brazil than EPIC. The K-factor estimates by the USLE nomograph ranges from 0.0002 to 0.0636 t ha h ha^{-1} MJ^{-1} mm^{-1}, with a mean value of 0.0181 t ha h ha^{-1} MJ^{-1} mm^{-1}. Our findings pave the way for a better understanding of soil erosion across multiple scales and thereby contributing to better land-use planning and management in Brazil. The dataset is freely available at https://doi.org/10.5281/zenodo.4279869

Keywords: Water erosion; RUSLE; K-factor; soil degradation; soil conservation.

RESUMO

Godoi, R. F., Rodrigues, D. B. B., Borrelli, P., Oliveira, P. T. S. (2021). **High-resolution soil erodibility map of Brazil**. *Science of The Total Environment, 781, 146673.* https://doi.org/10.1016/j.scitotenv.2021.146673

A modelagem da erosão do solo em larga escala tem um papel crucial na compreensão e planejamento de estratégias de conservação do solo e da água. A falta de dados espaciais de características do solo necessários para calcular a erodibilidade do solo (fator K) tem sido um dos maiores obstáculos no Brasil. O fator K é uma propriedade complexa que expressa a suscetibilidade do solo à erosão de acordo com suas características inerentes. Este fator é um parâmetro de entrada chave para os modelos de erosão do solo mais difundidos: a Equação Universal de Perda de Solo (USLE) e a USLE Revisada (RUSLE). Neste trabalho nós produzimos um mapa de erodibilidade espacialmente explícito de alta resolução (tamanho de célula de 250 m) para todo o Brasil. Para calcular o fator K aplicamos as equações propostas originalmente no nomógrafo da USLE (*USDA-Agriculture Handbook*, **537**, 1978) e no modelo EPIC (*Journal of Soil and Water Conservation*, **38**, 381–383, 1983), usando as seguintes propriedades do solo: conteúdo de matéria orgânica, textura, estrutura e permeabilidade do solo. Para avaliar qualitativamente nosso mapa do fator K, seus valores foram comparados com os valores do fator K obtidos de parcelas-padrão em todo o Brasil. Descobrimos que o nomógrafo USLE leva a uma estimativa mais precisa do fator K do que o modelo EPIC. As estimativas do fator K pelo nomógrafo USLE variam de 0,0002 a 0,0636 t ha h ha^{-1} MJ^{-1} mm^{-1}, com um valor médio de 0,0181 t ha h ha^{-1} MJ^{-1} mm^{-1}. Nossas descobertas abrem caminho para um melhor entendimento da erosão do solo em várias escalas e, assim, contribuem para um melhor planejamento e gestão do uso da terra no Brasil. O conjunto de dados está disponível gratuitamente em https://doi.org/10.5281/zenodo.4279869

Palavras-chave: Erosão hídrica; RUSLE; Fator K; degradação do solo; conservação do solo.

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LIST OF ABBREVIATIONS AND ACRONYMS

Embrapa – Empresa Brasileira de Pesquisa Agropecuária

FAO – Food and Agriculture Organization of the United Nations

ISRIC – International Soil Reference and Information Centre

K_{EPIC} – K-factor estimated by the EPIC model

K_{nomo} – K-factor estimated by the USLE nomograph

OECD – Organization for Economic Cooperation and Development

RUSLE – Revised Universal Soil Loss Equation

SOC – Soil organic carbon

SOM – Soil organic matter

USDA – United States Department of Agriculture

USLE – Universal Soil Loss Equation

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GENERAL INTRODUCTION

Soil erosion is a primary cause of soil degradation as it harms important soil functions within the Water-Food-Energy Nexus (Amundson et al., 2015). Therefore, large scale soil erosion modeling has a crucial role in the understanding and planning of soil and water conservation, with the purpose of maintaining water, food, and energy security. Moreover, the lack of soil erosion data impairs the discussion on environmental and agricultural policies to achieve global sustainability goals (Alewell et al., 2019).

The soil erodibility (K-factor) is a complex property that expresses the susceptibility of soil to erode according to its inherent characteristics. This factor is a key input parameter for the most widely applied soil erosion models. The K-factor can be determined directly by associating the measured soil loss with the rainfall erosivity index, however, this procedure is expensive and time-consuming (Nearing et al., 2000). As a result, there are few and sparse studies in Brazil that aim to directly determine the soil erodibility, and fewer that consider long-time data series.

Soil erosion models have been proposed since the 1900s (Borrelli et al., 2020). Among all the erosion models, the algebraic approximation of the USLE's nomograph by Wischmeier & Smith (1978) is the most used method to estimate K-factor. Despite its wide use, the nomograph equation requires information on soil structure and profile permeability, which are not easily assessed, making need of approximations and increasing uncertainty. Thus, alternative equations that exclude these information have been developed, such as the EPIC model by Williams et al. (1983). EPIC estimates the soil erodibility from only soil texture and organic carbon content.

A high-resolution mapping of K-factor will contribute to regional and local applications, as it can be used by researchers as input for erosion models, or for validation and comparison to their modeled or measured K-factor estimates. The identification of critical K-factor areas can also be a guide for better planning soil use and applying conservation practices (Panagos et al., 2015).

In this master's thesis we assess the soil erodibility of Brazilian soils. To compute a high-resolution (250 m cell size) spatially explicit soil erodibility map across Brazil we use the equations originally proposed in the USLE nomograph (Wischmeier and Smith,

1978) and EPIC model (Williams et al., 1983). To qualitatively evaluate our K-factor map, the estimated values are compared against standard K-factor values obtained from experimental plots across Brazil.

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OBJECTIVES

General objective

The main objective of this study is to assess the soil erodibility of Brazilian soils.

Specific objectives

i. To calculate the mean soil erodibility (K-factor) of Brazilian soils by the USLE nomograph equation.
ii. To calculate the mean K-factor of Brazilian soils by the EPIC model.
iii. To compare the resulting erodibility obtained by the two equations (USLE nomograph and EPIC model).
iv. To compile literature records of K-factor values determined experimentally in Brazil.
v. To validate the estimated K-factor against local measurements from experimental plots.
vi. Produce a high-resolution erodibility map of Brazil.

1. Introduction

Soil erosion is one of the main global threats to water and food security (Amundson et al., 2015). Soil provisioning, regulatory, and supporting services are essential for sustaining water, food, and energy security nexus (Keesstra et al., 2016). These services are carried out by soil functions that, in turn, are dictated by the condition of the soil resource, mainly by the soil organic matter (SOM) (Hatfield et al., 2017). SOM is related to soil biodiversity, supports water retention in the soil, improves soil structure and cation exchange capacity, and is the major source of nutrients needed by plants (Pimentel and Pimentel, 2008). Most of the soil organic matter is found close to the soil surface, thereby the removal of the topsoil layer significantly affects soil ecosystem services (Pereira et al., 2018).

The degradation of soil quality harms important soil functions within the water cycle, such as storage, sorptivity, and filtering. The results are increased sediment load for surface waters, pollution of water streams with sediment and nutrients, and siltation (Carpenter et al., 1998). In addition, by reducing soil storage capacity the risk of floods rises. More than 99% of human food comes from the land (Pimentel, 2006). Once soil fertility decreases with water erosion, it adversely affects food security by compromising agricultural production. It is estimated that water erosion reduces global agricultural food production by 33.7 million tonnes, being that for Brazil, a leading international food supplier (OECD-FAO, 2015), the losses are estimated as 8.2 million tonnes (Sartori et al., 2019). Therefore, soil erosion in Brazil is a threat that affects not only its domestic market but global food security.

The projected decrease in rainfall patterns over the North, Northeast, Central-West, and Southeast regions of Brazil encourages the expansion of agricultural production in these regions, supporting food security (Almagro et al., 2017). However, this expansion may result in the conversion of natural land cover to croplands and pasture, increasing the soil loss rate (Oliveira et al., 2015). While in the South, the projected increase in rainfall erosivity tends to affect food production by increasing soil loss rate and consequently decreasing soil fertility (Almagro et al., 2017). The effects of climate change on rainfall erosivity patterns in Brazil highlight the need of creating strategies and public policies of soil management aiming to ensure water, food, and energy security.

Another issue that has raised concern for food security is the effects of water erosion associated with the dependency on chemical phosphorus (P) fertilizers from non-renewable P deposits. Alewell et al. (2020) highlight that water erosion explains over 50% of the total P loss worldwide. Even with a high surplus P accrued in Brazilian soils from fertilizers, over 70% are not readily available to crops (Pavinato et al., 2020). Water erosion is related to the P loss both by decreasing soil fertility and by leading to the eutrophication of water bodies as P is deposited.

In the context of energy security, secure soil is the foundation for the production of renewable energy sources (e.g. crops for biofuels and water reservoirs for hydropower plants) (McBratney et al., 2014). Almost 83% of energy production in Brazil comes from renewable sources, being that hydroelectric generation is responsible for 63% (ANEEL, 2020). Hydropower generation depends significantly on the hydrological availability, which can be threatened by reduced soil storage capacity and increased sediment load of rivers (Dias et al., 2018).

Large-scale mapping of soil erosion is essential and urgent for earth science system modeling with the purpose of maintaining water, food, and energy security. The lack of soil erosion data impairs the discussion on environmental and agricultural policies to achieve global sustainability goals (Alewell et al., 2019). Therefore, to better understand and plan soil water conservation on multiple scales, soil erosion models have been proposed since the 1900s (Borrelli et al., 2020b).

The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and its revised version (RUSLE) (Renard et al., 1997) are the most widespread models for estimating long-term average annual soil loss and for soil and water conservation planning (Borrelli et al., 2020b). The RUSLE is composed of six factors, a resistance term (K, soil erodibility factor), a driving force (R, rainfall and runoff factor), and other four factors representing the farming choice, topographical conformation of the field (LS, slope-length and slope-steepness factor), cropping system (C, cover and management factor) and soil conservation practices (P, supporting practice factor) (Wischmeier and Smith, 1978).

The rate of soil erosion diverges for different soils when slope, rainfall, cover and management factors are the same; this difference results from the soil properties only and represents the soil erodibility (Wischmeier and Smith, 1965). The K-factor is experimentally determined by associating the soil loss with the rainfall erosivity index. This procedure is carried out in standard plots, which are 22.1 meters long, on a 9% slope under a continuous bare cultivated fallow, tilled in the slope direction, under natural rain, with data collected for at least 5 years, beginning 2 years after the clean-fallow condition was established (Wischmeier and Smith, 1978).

Although direct measurements are the most reliable way to determine soil erodibility, this method is expensive and time-consuming (Nearing et al., 2000). In several countries, available measured data in experimental plots are still scarce or inexistent (Morgan, 2005). For instance, field plot studies started in the 1940s and increased until 2000 in Brazil, from 2000 onwards the studies experienced a decrease of about 86% in the following 15 years (Anache et al., 2017). As a result, there are few and sparse studies that aim to directly determine soil erodibility, and fewer that consider long-time data series.

The restraints of direct measurements motivate researchers to develop mathematical methods for estimating soil erodibility from more easily measurable soil properties. The algebraic approximation of the USLE's nomograph for example is the most used method to estimate K-factor. The equation has been used to predict global-scale soil loss and its impacts (Borrelli et al., 2017; Sartori et al., 2019; Borrelli et al., 2020a). Despite its wide use, the nomograph equation requires information on soil structure and profile permeability, which are not easily assessed, making need of approximations and increasing uncertainty. Thus, alternative equations that exclude these information have been developed, such as the EPIC model by Williams et al. (1983). EPIC estimates the soil erodibility from only soil texture and organic carbon content.

There are some reports that locally investigate soil erodibility by both direct and indirect methods in Brazil (e.g., Cogo et al., 2003; Hernani et al., 1997; Silva et al., 2009; Martins Filho et al., 2009; Silva et al., 2000; Albuquerque et al., 2005; Marques et al., 1997), but there are no large-scale studies focusing on soil erodibility. The lack of spatial soil characteristics data has been one of the greatest obstacles in large-scale erosion mapping in Brazil.

A large-scale mapping of K-factor will contribute to regional and local applications. Panagos et al. (2014) have estimated soil erodibility for Europe and the dataset has been used by researchers as input for erosion models, or for validation and comparison to their modeled or measured K-factor estimates. The identification of critical K-factor areas can also be a guide for better planning soil use and applying conservation practices (Panagos et al., 2015).

Therefore, the objective of this study is to produce a high-resolution soil erodibility map for Brazil (with a grid cell size of 250 m). The results obtained by the two equations proposed originally in the USLE and EPIC are compared. Besides the high resolution dataset of soil properties such as organic matter content and soil texture, soil structure and permeability are also considered. We evaluate the estimated K-factor values against local measurements from experimental plots.

2. Materials and methods

2.1. Input data

Soil content of clay, sand, silt, and organic matter data for the 0 cm to 30 cm depth interval were acquired from ISRIC SoilGrids (Hengl et al., 2014). SoilGrids is a system that provides global digital soil mapping at 250 m resolution, based on a global compilation of soil profile data. Data for Brazil were modeled from 8,888 soil profiles. Systematized information about soil groups were obtained from the Brazilian Soil Classification System (SiBCS) (Embrapa, 2018) and conformed to the World Reference Base (FAO, 2015). Summarized methodology is presented in the diagram below (Figure 1).

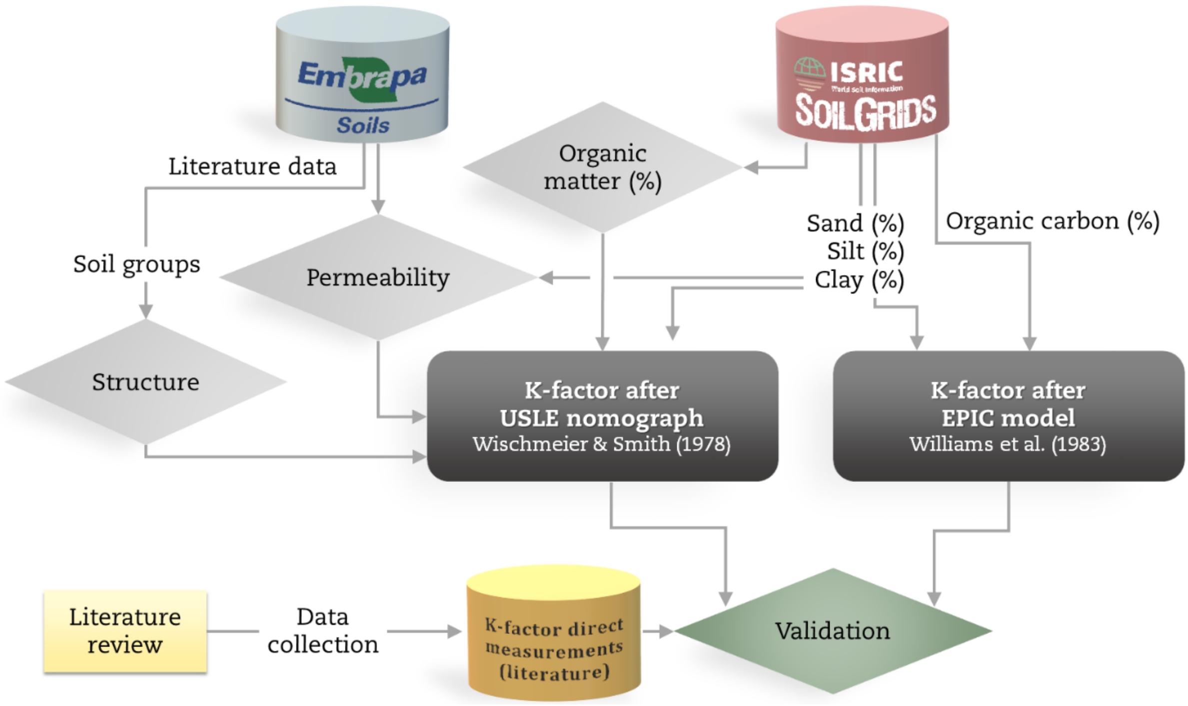

Fig. 1. Summary of the methodology applied to estimate soil erodibility for Brazilian soils.

2.2. Estimation of soil erodibility by USLE nomograph

Soil erodibility can be expressed algebraically as a function of the particle-size parameter, percent organic matter, soil-structure code, and profile-permeability class (Wischmeier and Smith, 1978; Renard et al., 1997). This equation works only for soils which silt content does not exceed 70%:

$$K_{nomo} = \{(2.1M^{1.14} \times 10^{-4} \times (12 - SOM) + 3.25 \times (s - 2) + 2.5 \times (p - 3)) \div 100\} \times 0.1317 \quad \text{(Eq. 1)}$$

where:

K_{nomo}: soil erodibility (t ha h ha^{-1} MJ^{-1} mm^{-1})

M: particle-size parameter, with M = (silt + vfs) × (100 − clay);

clay: clay fraction content (< 0.002 mm) (%);

silt: silt fraction content (0.002–0.05 mm) (%);

vfs: very fine sand fraction content (0.05–0.1 mm) (%);

SOM: soil organic matter content (%);

s: soil structure code (Table 1);

p: soil permeability code (Table 2);

and 0.1317 is the SI metric unit conversion factor.

As mentioned before, information on clay, silt, sand and organic carbon content of soil (SOC) were acquired from SoilGrids. Silt content was limited to 70% since it is a requisite for applying USLE nomograph equation (Eq. 1). The very fine sand fraction is not commonly subject to standard soil analysis and was therefore estimated as 20% of the sand fraction, following Panagos et al. (2014).

The oxidation degree of organic matter is greater in tropical soils than in temperate regions, making the SOM/SOC ratio for Brazilian soils higher than the commonly recommended factor of 1.724 (Bianchi et al., 2008; Miyazawa et al., 2000; Conceição et al. 1999). Following Pribyl (2000), we adopted a conversion factor of two to estimate soil organic matter from soil organic carbon, that assumes that 50% of soil organic matter (SOM) is composed of organic carbon (SOC). An upper limit of 4% was set for organic matter as recommended by the US Department of Agriculture's National Soils Handbook No. 430 (USDA, 1983). This limit prevents underestimating soil erodibility for soils that are rich in organic matter.

2.2.1. Structure code estimation

Soil structure is a complex property that describes the shape and the size of soil particles and the way they arrange to form aggregates. Well-structured soils with a high degree of aggregate stability evince improved soil fertility and diminished erodibility (Bronick and Lal, 2005).

Due to its dynamic interactions with environmental and anthropogenic factors, measuring soil structure is extremely difficult and there is no universally accepted way to characterize soil structure (Díaz-Zorita et al., 2002). Since there are no previous studies aiming to map information on the structure of soils in Brazil, we resorted to the literature description for each soil group. Structure classes were then assigned to soil groups mapping by Embrapa (2012) (Table 1).

Table 1. Classes of soil structure set for soil groups.

Structure class	Soil groups
1 - very fine granular	ferralsols
2 - fine granular	acrisols and plinthosols
3 - medium or coarse granular	podzols; luvisols; fluvisols; leptosols; arenosols; regosols; and planosols.
4 - blocky, platy or massive	cambisols; chernozems; gleysols; nitisols; histosols; vertisols

2.2.2. Estimation of permeability class

Soil permeability is a function of soil texture, structure, and bulk density and describes the velocity at which water percolates through the soil. Water quickly enters highly permeable soils, reducing runoff and consequently soil erosion. For the estimation of the soil permeability, classes were assigned according to the soil texture classes described in the Brazilian Soil Classification System (Embrapa, 2018).

Table 2. Classes of soil permeability.

Permeability class	Texture
1 - rapid	sand
2 - moderate to rapid	loamy sand, sandy loam
3 - moderate	sandy clay loam, silty loam
4 - slow to moderate	silty
5 - slow	clayey
6 - very slow	very fine clayey

2.3. Soil erodibility estimated by the EPIC model

EPIC (Erosion-Productivity Impact Calculator) was specifically designed for determining the relationship between soil erosion and soil productivity (Williams et al., 1983). This model consists of numerous physical components that describe the erosion/productivity relationship. Besides water erosion, EPIC model components include hydrology, nutrient dynamics, plant growth, soil temperature, tillage, and economics.

The calculation of soil erosion by water is based on USLE, i.e., by the multiplication of the six aforementioned factors and including the coarse fragment factor. Soil erodibility is given simply by the relation of soil particle size and the organic carbon content. Equation 2 allows K to vary from about 0.1 to 0.5 (0.0132 to 0.0659 in SI metric units) and is expressed as:

$$K_{EPIC} = (0.2 + 0.3exp(-0.0256SAN(1 - SIL/100))) \times \left(\frac{SIL}{CLA + SIL}\right)^{0.3} \times (1 - (0.25SOC/(SOC + exp(3.72 - 2.95SOC)))) \times (1 - (0.7SN/(SN + exp(-5.51 + 22.9SN)))) \times 0.1317 \quad \text{(Eq. 2)}$$

where:

- K_{EPIC}: soil erodibility (t ha h ha^{-1} MJ^{-1} mm^{-1})
- CLA: clay fraction content (< 0.002 mm) (%);
- SIL: silt fraction content (0.002–0.05 mm) (%);
- SAN: sand fraction content (0.05–2.0 mm) (%);
- SOC: soil organic carbon (%);
- SN: 1 - SAN/100;

and 0.1317 is the SI metric unit conversion factor.

Input data for soil texture and soil organic carbon for the 0 cm to 30 cm depth interval came from SoilGrids. In order to consistently compare the results, EPIC input data had the same approaches as the USLE nomograph, that is: organic carbon limited to 2% (i.e., SOC = SOM/2), following the Handbook No. 430 (USDA, 1983), and very fine sand fraction (considered as 20% of sand fraction) added to silt fraction, following Panagos et al. (2014).

2.4. Observed data of soil erodibility

We reviewed the ISI Web of Science, SciELO, and Google Scholar databases looking for records with the terms "erodibility", "K-factor", and "Brazil" in the period of 1982 to July 2020. We considered records from scientific journal publications, conference papers, M.Sc. theses, Ph.D. dissertations, books and also gray literature.

We organized a database of observed soil erodibility containing information about soil type, rain method, plot site, initial and final time of experiment. We collected data of both natural and simulated rainfall in different areas of the five regions of Brazil.

2.5. Validation and comparison of modeled K-factor

The K-factor values estimated by USLE and EPIC models were validated against collected data of locally measured erodibility. The difference between observed and estimated K-factor was evaluated by the non-parametric Mann-Whitney test with a 95% confidence level. To compare the modeled results, we computed the relative difference (Equation 3). The percent error (Equation 4) and the root-mean-square error (RMSE) (Equation 5) were applied to assess the error between observed and estimated values.

$$relative\ difference = \frac{|K_{EPIC} - K_{nomo}|}{K_{nomo}} \quad \text{(Eq. 3)}$$

where K_{nomo} and K_{EPIC} are the soil erodibility values computed by Equation 1 and Equation 2, respectively.

$$percent\ error = \frac{|K_{est} - K_{obs}|}{K_{obs}} \quad \text{(Eq. 4)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(K_{est} - K_{obs})^2}{n}} \quad \text{(Eq. 5)}$$

where K_{est} and K_{obs} refer to the values estimated in the present study and those collected from literature, respectively.

3. Results and discussion

3.1. Soil erodibility predicted by USLE nomograph and EPIC model

A summary of the input data and resulting K-factor is presented in Table 3. The erodibility maps predicted by the nomograph and by the EPIC model are presented in Figure 2. Comparing the values of soil erodibility estimated for Europe (mean value of 0.032 t ha h ha-1 MJ-1 mm-1) (Panagos et al., 2014), both methods result in lower mean values for Brazil. The mean K-factor of Brazil is also lower than the sampled soils in the United States, where the range is 0.0039 – 0.0910 t ha h ha-1 MJ-1 mm-1 and the mean value is 0.0379 t ha h ha-1 MJ-1 mm-1 (Wischmeier and Smith, 1978). Zhang et al. (2008) found a mean erodibility value of 0.0144 t ha h ha-1 MJ-1 mm-1 for Chinese soils, lower than the estimated for Brazil. Knomo and KEPIC results for each soil group are presented in Figure 3.

Table 3. Summary of the input data and resulting K-factor.

Attibute	Range	Mean value	Standard deviation
Silt content	0-70%	25.30%	9.79%
VFS	0-20%	8.54%	2.83%
Clay content	0-100%	30.04%	8.54%
Structure	1, 2, 3, 4	2*	
Permeability	1, 2, 3, 4, 5, 6	3*	
SOM	0-4%	3.87%	0.58%
SOC	0-2%	1.93%	0.29%
K_{nomo} (t ha h ha^{-1} MJ^{-1} mm^{-1})	0.0002-0.0636	0.0181	0.0065
K_{EPIC} (t ha h ha^{-1} MJ^{-1} mm^{-1})	0.0209-0.0576	0.0307	0.0034

* Predominant value

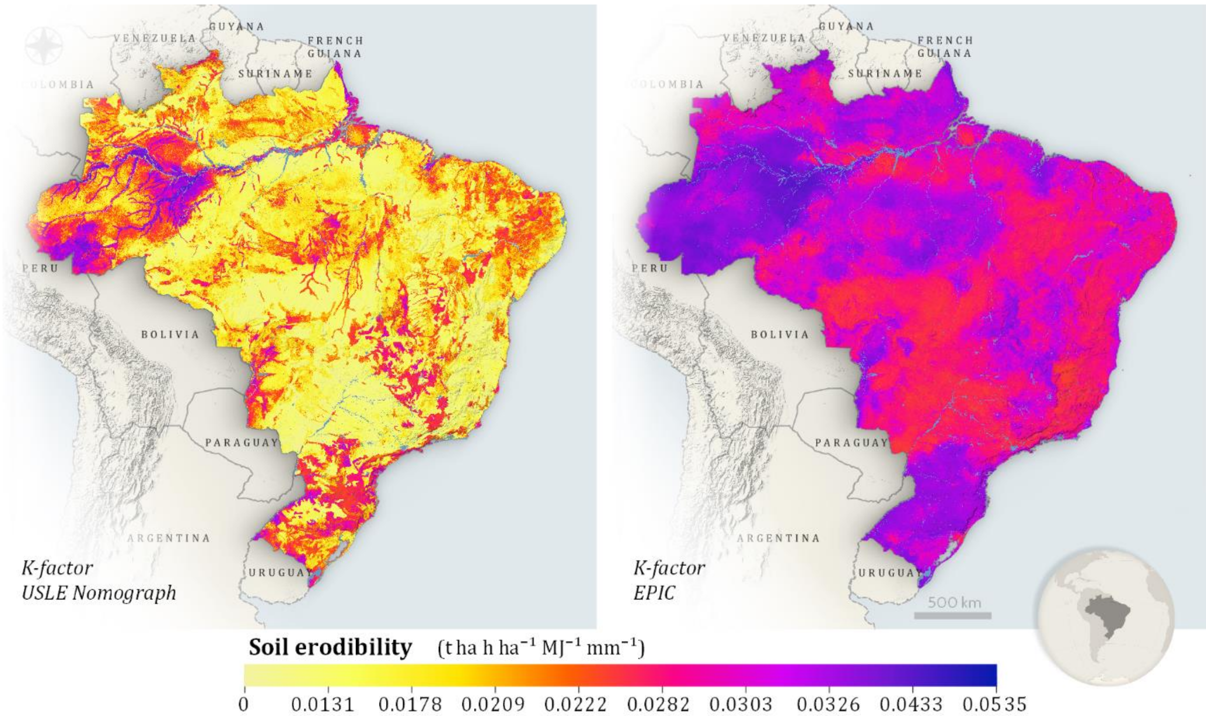

Fig. 2. Soil erodibility predicted by USLE nomograph (left) and by EPIC model (right). Both models present similar results concerning spatiality. In general, EPIC predicts higher values than USLE nomograph.

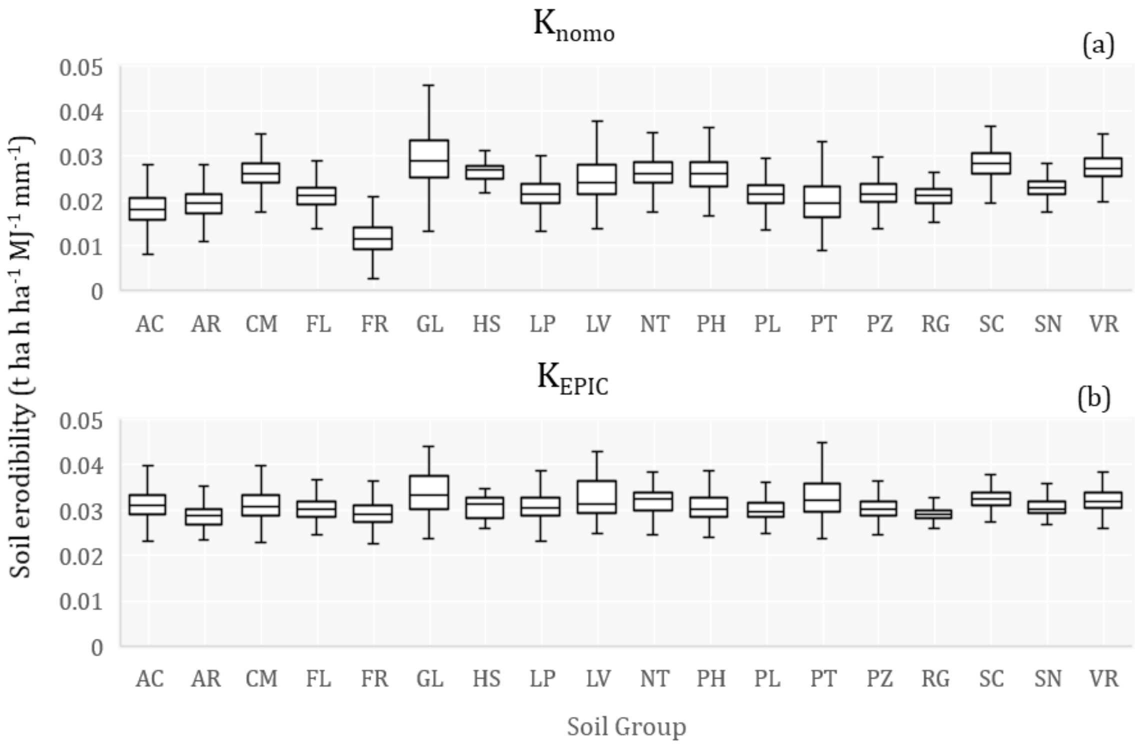

Fig. 3. Soil erodibility estimated for each soil group by USLE nomograph (a) and EPIC (b). Box = 25th and 75th percentiles; line in the middle of the box = median; bars = min and max values. AC – Acrisols; AR – Arenosols; PH – Phaeozems; CM – Cambisols; PZ – Podzols; FL – Fluvisols; FR – Ferralsols; GL – Gleysols; HS – Histosols; LP – Leptosols; LV – Luvisols; NT – Nitisols; PL – Planosols; PT – Plinthosols; RG – Regosols; SC – Solonchaks; SN – Solonetz; VR – Vertisols.

Comparing the results by the relative difference, we observe that EPIC predicts higher values than the USLE nomograph for the whole country. In 65% of the territory, the difference varies from 10% to 100%. Structure is the component with the highest correlation with the difference (ρ=-0.76, inverse correlation), hence the highest difference values occur in soil units where the structure code is 1 (very fine granular) (Figure 4).

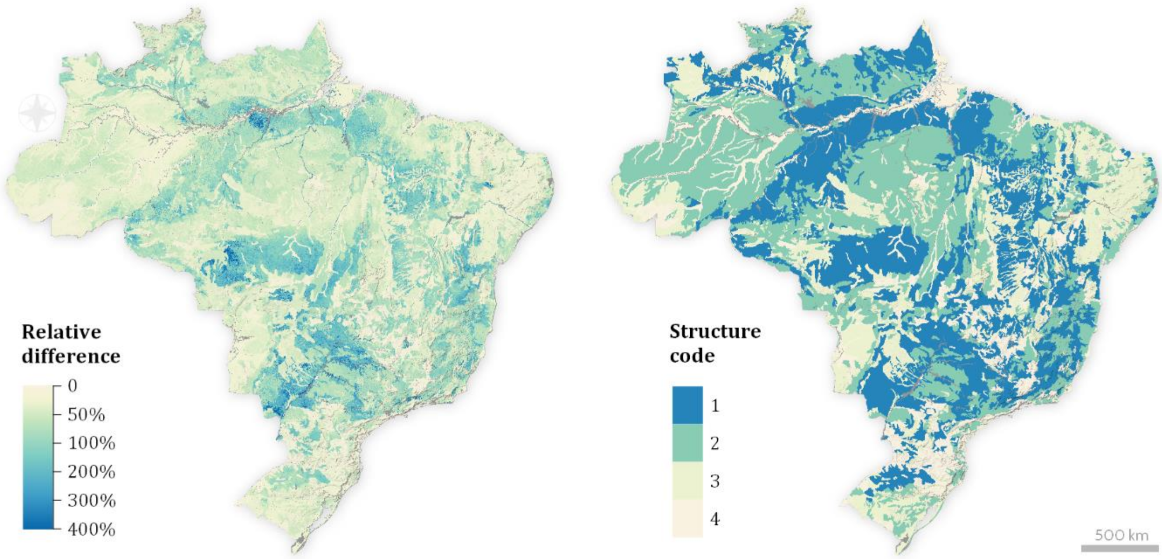

Fig. 4. Relative difference of soil erodibility predicted by USLE nomograph and by EPIC model. There is a strong negative correlation between the relative difference and the soil structure code.

3.2. Compilation of plot-scale erodibility studies

We found 33 studies, distributed in 50 municipalities, resulting in 92 values for soil erodibility direct measurements (Figure 5 and Tables S1 and S2 in the Appendices). South – S, Northeast – NE and Southeast – SE Regions comprise 38%, 26% and 24% of the field studies, respectively. The North – N Region, the largest in territory, represents only 2%. The concentration of studies in Southern and Southeastern Brazil can be explained by the high population density and the economic importance of these regions (Oliveira et al., 2013), which together sum 51% of Brazil's agricultural GDP. Research on soil erosion intensified in the 1980s and 1990s in the Northeast by the partnership between Federal universities and the Brazilian Agricultural Research Corporation – Embrapa (Barretto et al., 2008).

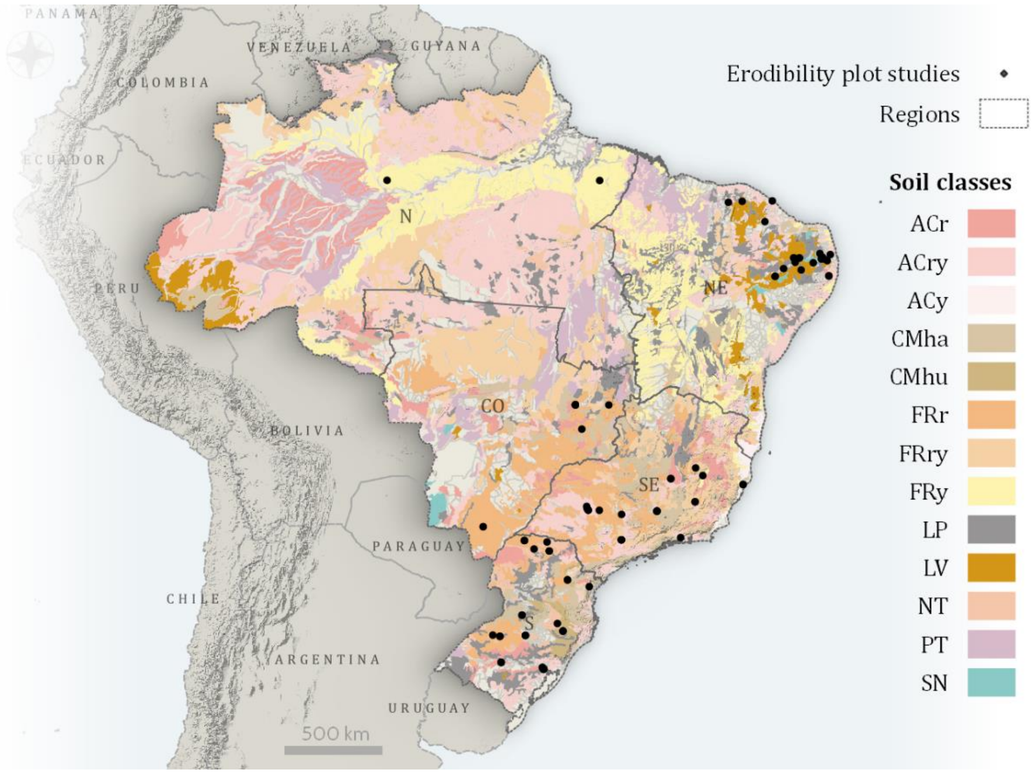

Fig. 5. Spatial distribution of erodibility field studies in Brazil. Ferralsols and acrisols concentrate the highest number of studies. The highest number of studies are in the South, Northeast and Southeast. N – North; NE – Northeast; CO – Central-West; SE – Southeast; and S – South. ACry – Acrisol (red yellow); ACr – Acrisol (red); ACy – Acrisol (yellow); CMha – Cambisol (haplic); CMhu – Cambisol (humic); FRry – Ferralsol (red yellow); FRr – Ferralsol (red); FRy – Ferralsol (yellow); LP – Leptosol; LV – Luvisol; NT – Nitisol; PL – Planosol; PT – Plinthosol.

Ferralsols and acrisols together occupy 58% of the Brazilian territory and are the soil types with the greatest number of studies. Of the 18 soil groups, we found erodibility reports for only 8. For more solid results, we specified the subclasses of acrisols, cambisols and ferralsols. From the compiled dataset of soil erodibility, we determined the mean K-factor values for each of the sampled soil types (Figure 6).

To achieve accurate direct measurement of K-factor from unit plots, it is recommended to collect soil loss data under natural rain for at least 5 years after leaving the plot in clean-fallow condition for 2 years (Wischmeier and Smith, 1978, p. 57). Rainfall simulators allow quicker and less costly K-factor evaluations, but they may not truly represent natural rain erosive patterns. Of the total 95 records, 48 were determined under natural rainfall and 35 under simulated rain. For the other 12 values of K-factor it was not possible to determine either the time of data collection or the method of rain. Of the 31 erodibility values determined under natural rainfall, 16 were obtained from time series longer than 5 years.

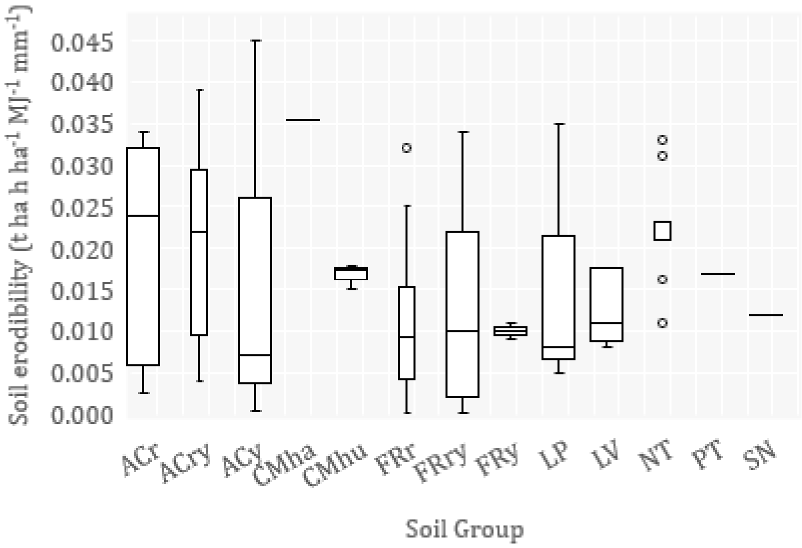

Fig. 6. K-factor values for different types of soils with field determination. Box = 25th and 75th percentiles; line in the middle of the box = median; bars = min and max values; points = K-factor direct measurements. ACry – Acrisol (red yellow); ACr – Acrisol (red); ACy – Acrisol (yellow); CMha – Cambisol (haplic); CMhu – Cambisol (humic); FRry – Ferralsol (red yellow); FRr – Ferralsol (red); FRy – Ferralsol (yellow); LP – Leptosol; LV – Luvisol; NT – Nitisol; PL – Planosol; PT – Plinthosol; SN – Solonetz.

3.3. Validation and comparing the estimated erodibility values

As pointed by Alewell et al. (2019), the process of validation of USLE-type applications is usually carried out in the most rigorous possible way, i.e., even though the model algorithms are not calibrated, the resulting outputs are compared to measured data. We must accept that there is some uncertainty concerning the accuracy of the reported K values, even though, observations will always be closer to the truth than modeling and must remain the most important component of scientific investigation (Wainwright and Mulligan, 2004).

Comparing the K-factor values estimated by the USLE nomograph with the measured ones for each soil group we found that there is no significant difference between K_{nomo} and K_{obs} for most soil types ($p > 0.05$), we noted a significant difference only for humic cambisols and nitisols. In view of K_{EPIC} the estimated values were significantly different from the observed ones ($p < 0.05$) for all of the sampled soil types except by yellow acrisols, haplic cambisols, leptosols and solonetz (Table 4 and Figure 7).

Table 4. Mann-Whitney U test results for estimated values.

	U_{nomo}	U_{EPIC}	p_{nomo}	p_{EPIC}	n_{obs}	n_{est}
ACr	19609	9529	0.596	0.001*	11	3929
ACry	120365	59235	0.369	0.000*	19	14384
ACy	253	253	0.323	0.323	3	253
CMha	90	369	0.101	0.173	1	3469
CMhu	6	0	0.003*	0.003*	3	292
FRr	71420	4717	0.561	0.000*	30	5073
FRry	19402	8191	0.745	0.018*	5	8472
FRy	4599	0	0.292	0.014*	2	8078
LP	4996	4704	0.317	0.264	3	4998
LV	1792	1080	0.061	0.012*	4	1956
NT	1793	727	0.010*	0.000*	9	792
PT	1396	0	0.475	0.083*	1	4758
SN	0	0	0.086	0.086	1	266

A regular point grid of 0.1° × 0.1° spacing was created to sample estimated K-factor values. This way, the sample size of each soil group is proportional to its occurrence in the Brazilian territory. U_{nomo} – U-value resulting from Mann-Whitney test for K_{nomo} and K_{obs}; U_{EPIC} – U-value resulting from Mann-Whitney test for K_{EPIC} and K_{obs}; p_{nomo} – p-value for Mann-Whitney test for K_{nomo} sample; p_{EPIC} – p-value for KEPIC sample; n_{obs} – sample size for observed K-factor; n_{est} – sample size for estimated K-factor; * Significant difference between estimated and observed K-factor at a confidence level of 95%. ACry – Acrisol (red yellow); ACr – Acrisol (red); ACy – Acrisol (yellow); CMha – Cambisol (haplic); CMhu – Cambisol (humic); FRry – Ferralsol (red yellow); FRr – Ferralsol (red); FRy – Ferralsol (yellow); LP – Leptosol; LV – Luvisol; NT – Nitisol; PL – Planosol; PT – Plinthosol; SN – Solonetz.

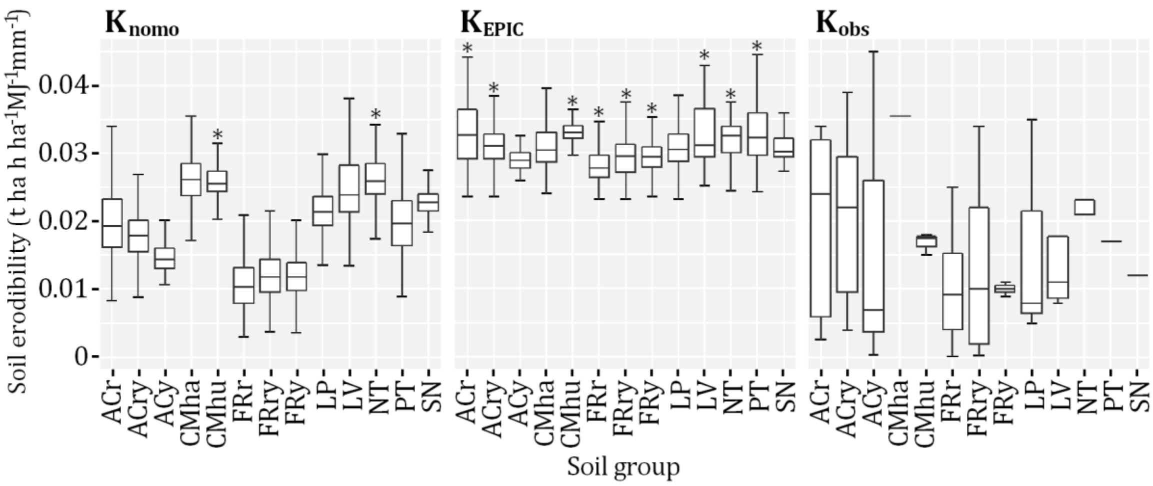

Fig. 7. Soil erodibility predicted by USLE nomograph (left) and EPIC model (middle) and direct measurement values (right). Box = 25th and 75th percentiles; line in the middle of the box = median; bars = min and max values; * significant difference between estimated and observed K-factor at a confidence level of 95%.

We found a RMSE of 0.0014 for K_{nomo} and of 0.0189 for K_{EPIC} (see more in Table S3 in the Appendices). The K-factor values estimated by EPIC are in a higher range than the observed values, making the error greater for this model. Concerning the rain method, we found no significant difference between the error for observations under natural and simulated rain. In fact, the highest error is found for a red-yellow ferralsol, of which the only observation under natural rain has a low order of magnitude, which enhances the relative error.

When plotting the results by soil group, it is clear to see that K_{nomo} approximates to K_{obs} better than K_{EPIC} (Figure 8). K_{nomo} estimates are especially good for those soil groups with the greatest number of samples, acrisols and ferralsols. Haplic cambisol is the only soil class for that K_{EPIC} estimate is closer to the observed value than K_{nomo}. The observed value for this class was estimated by a single report of 4.9 years of observation, increasing uncertainty. When grouping all the observations for cambisols (Figure 8.b), the mean plot-year goes up to 9, taking K_{obs} closer to K_{nomo}.

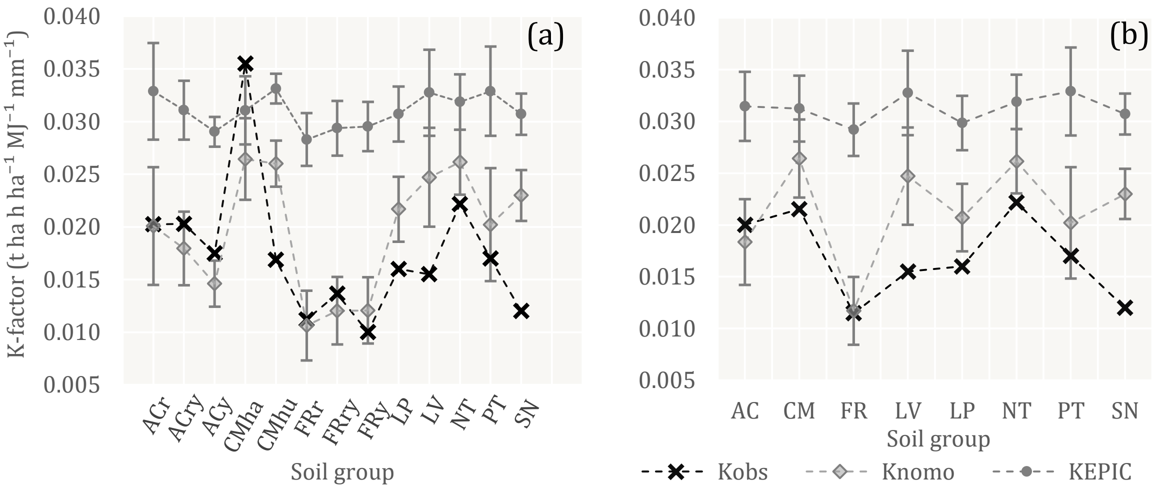

Fig. 8. (a) Comparison of K-factor estimates by USLE nomograph and EPIC with measured data. On (b), acrisols, cambisols and ferralsols classes are grouped. Both models in general overestimate soil erodibility, but K_{nomo} approximates to K_{obs} better than K_{EPIC}. Bars = standard deviation. AC– Acrisols; ACry – Acrisol (red yellow); ACr – Acrisol (red); ACy – Acrisol (yellow); CM – Cambisols; CMha – Cambisol (haplic); CMhu – Cambisol (humic); FR – Ferralsols; FRry – Ferralsol (red yellow); FRr – Ferralsol (red); FRy – Ferralsol (yellow); LP – Leptosol; LV – Luvisol; NT – Nitisol; PL – Planosol; PT – Plinthosol.

The error of K_{nomo} estimate for solonetz stands out. For this soil class, the K_{obs} value was also determined by a single observation, which we could not assess the rain method nor the plot experiment time. In contrast, the observed value for plinthosols was defined by a single report as well, but in this case, we know the time of experiment (6.5 years), making the assessment more reliable. This evinces the need for consistent experimental field data.

3.4. Interpretation of the resulting K-factor

For both models the highest values occur in Amazonas and Acre States (Figure 9), where silt content reaches the highest levels. The young sediments of the sedimentary Amazon basin, mainly in the floodplains and its tributaries, were formed during the Neogene and Quaternary periods (Gómez et al., 2019), and are easily eroded. The main soil types in this region are red acrisols, plinthosols, haplic gleysols, luvisols and cambisols. Although these soil types reach the highest values, their mean values for the whole country are significantly lower. That is why these groups have the highest standard deviation.

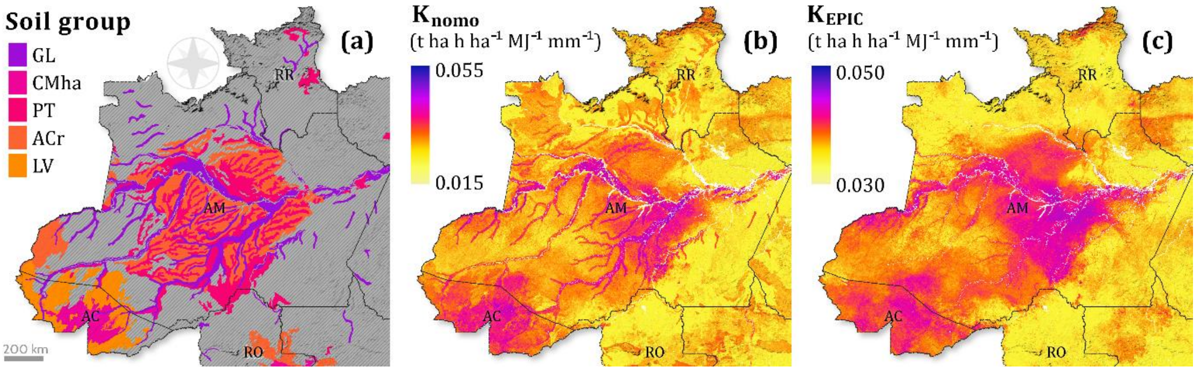

Fig. 9. The highest values predicted by K_{nomo} and K_{EPIC} occur in the Amazonas (AM) and Acre (AC) states. (a) Soil types where the highest values occur: GL – Gleysols; CMha – Haplic cambisols; PT – Plinthosols; ACr – Red acrisols; LV – Luvisols. (b) K-factor estimated by the USLE nomograph. (c) K-factor estimated by the EPIC model.

The soil group with higher susceptibility to erosion according to both methods are gleysols (GL). Gleysols occur mainly in depression areas nearby water streams, being permanently or periodically saturated with water. Most of GL occur in the North Region (83%), where high silt content associated with poor drainage and platy structure results in high soil erodibility. However, the potential of erosion is attenuated since these soils are commonly formed on flat terrain and are covered by riparian vegetation, which are protected by Brazilian law.

It is important to point that although deforestation in the Brazilian Amazon has significantly reduced since 2004 (INPE, 2020) political and economic changes generate uncertainties about the future of Brazilian environmental policies (Reydon et al., 2020).

In a scenario of weakening of environmental policies, areas in the Brazilian Amazon projected to be deforested by 2050 (Soares-Filho et al., 2006) coincide with high soil erodibility areas. The risk of deforestation in areas of high soil erodibility induces to the long-discussed importance of protecting the Amazon rainforest.

The lowest values estimated by the two models occur where ferralsols take place. Ferralsols (FR) are formed under intense weathering conditions, resulting in deep soils with good permeability and stable microstructure. As a rule, they are poor in silt, making them less susceptible to erosion than most other highly weathered tropical soils (FAO, 2015). However, FR generally have low water retention capacity and become highly erodible when subjected to intensive tillage and inappropriate cultivation systems (Hernani et al., 1997).

Ferralsols represent almost one third of Brazil's territory and perform important ecosystem services. In Northern Brazil, 83% of FR occur in the Amazon rainforest area, great part in protected areas. They are mostly found very poor in nutrients, thus extensive grazing is the main activity in the Central-West, Northeast and Southeast Regions. The lands with the best agricultural potential of FR are located in the south (Ramalho Filho and Pereira, 1999), allowing the cultivation of crops in this region (Figure 10).

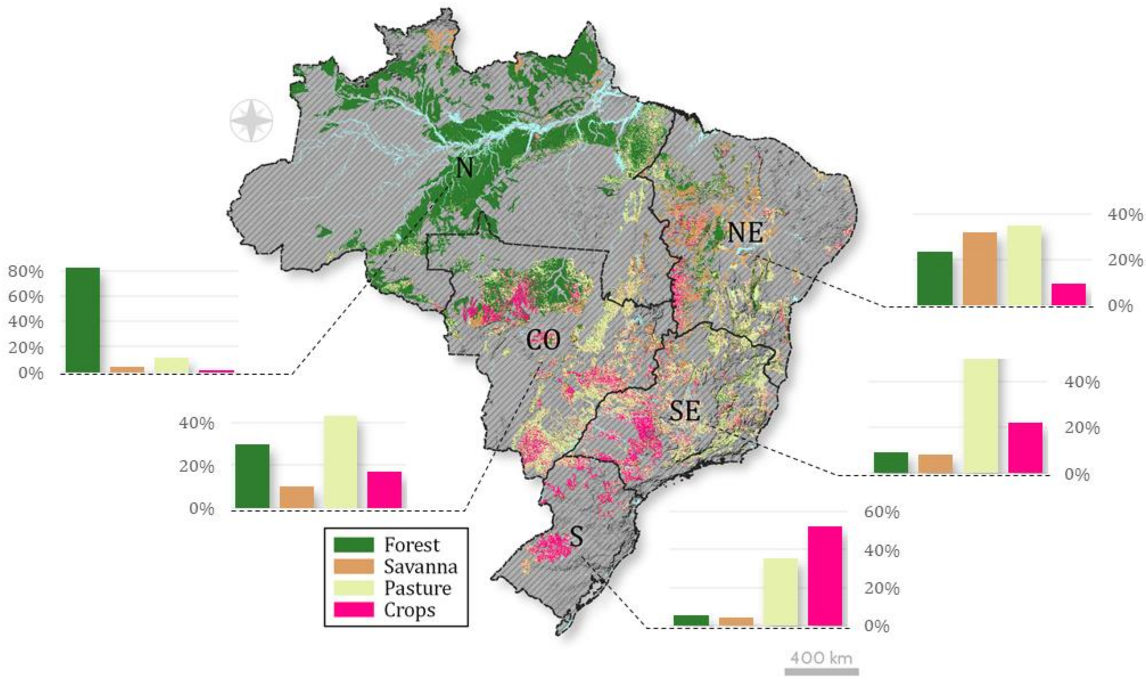

Fig. 10. Distribution and land use of ferralsols (FR) in Brazil. Great part of FR is located in the North Region, where they are primarily covered by forests. They are generally found naturally acid and unfertile, thereby pasture is a common activity. In the South and Southeast Regions, the

agricultural potential is better, allowing crop cultivation. Adapted from Soares-Filho et al. (2012). CO – central-west; N – north; NE – northeast; SE – southeast; and S – South.

Despite the similar tendencies, the USLE nomograph and the EPIC model diverge in some information. While ferralsols are the group with the lowest mean erodibility for K_{nomo}, K_{EPIC} estimates the lowest mean value for arenosols (AR). Both FR and AR are generally deep and high permeability soils. Even though they are easily detached, the low runoff results in resilience to erosion (FAO, 2015).

The correlation with sand and silt fraction in stronger for K_{EPIC} than for K_{nomo} ($p = -0.8092$ against $p = -0.5256$ for sand, $p = 0.9933$ against $p = 0.7070$ for silt, for K_{EPIC} and K_{nomo} respectively). AR have higher sand content and lower silt content than FR (Figure S1 in the Appendices), that is why K_{EPIC} results in the lowest values for arenosols. K_{nomo} has a significant correlation with soil structure ($p = 0.7691$). The USLE nomograph estimates the lowest erodibility values for ferralsols since this soil group have very fine granular structure, what results in low erodibility values. In addition, Bertol & Almeida (2000) found that FR have higher tolerance to erosion than AR.

Arenosols are essentially sandy and poor in organic matter, hampering aggregation and water retention (Costa et al., 2013). Therefore, soil management aiming to maintain or increase the levels of organic matter and the implementation of soil conservation practices are fundamental to contain erosion. AR major occurrence is in Central-West, with grazing as main activity. In the Northeast and Southeast Regions they occur in savanna areas and in forest areas in the North. Their occurrence is rare in the South.

Another discrepancy refers to plinthosols (PT), which is the group with the second highest mean value predicted by EPIC while for USLE nomograph the estimated mean value is among the lowest ones. Plinthosols are usually very differentiated soils, and the top layer can be of any type (Embrapa, 2018). A major part of PT in Brazil is located where silt content is high, which may explain the high mean value estimated by EPIC. In contrast, the low mean value estimated by the USLE nomograph can be explained by the assignment of the fine granular structure code. The definition of a fixed value for structure in a variable soil may increase uncertainties for the nomograph estimation. However, the lack of soil structure data requires assumptions.

Although the assignment of structure classes based on literature provided suitable results for the USLE nomograph K-factor estimation, the results could be improved by using more experimental data. Soil profile permeability was estimated based on soil texture, but could be improved by a more meticulous study. The fraction of very fine sand is another subject that requires additional investigation for the Brazilian soils. Experimental plot studies are essential to validate modeled information on soil erosion and should be encouraged by research institutions.

4. Conclusions

This study compares two widespread erosion models to determine the soil erodibility in Brazil, validating results against a database of measured K-factor. Our study includes soil structure and permeability information (for the USLE nomograph). The development of a high-resolution erodibility map is an important contribution to erosion research in Brazil, since K-factor is an essential information to estimate soil loss by the USLE/RUSLE and other erosion models. The erodibility dataset can also be used for validation and comparison to modeled or measured K-factor estimates. Moreover, the K-factor map can help diverse environmental applications, allowing a better planning and management of soil resources in Brazil, guiding the implementation of better conservation practices.

EPIC model tries to simplify the erodibility determination excluding soil structure and permeability. These important soil characteristics are difficult to assess, but seems to be required to a more reliable erodibility evaluation. EPIC overestimates erodibility for all the soil groups that occur in Brazil. Although the USLE nomograph also overestimates for most soil types, the predicted values are notably closer to the measured reports. Thus, we found that the algebraic solution of USLE nomograph leads to more precise estimations of K-factor. K-factor estimates by USLE nomograph range from 0.0002 to 0.0636 t ha h ha^{-1} MJ^{-1} mm^{-1}, with a mean value of 0.0181 t ha h ha^{-1} MJ^{-1} mm^{-1}. Soil erodibility for Brazilian soils is lower than in Europe and in the United States, and higher than Chinese soils.

We found critical areas and the soil groups most susceptible to soil erosion. The highest erodibility values occur in Western Amazon, where forests are the main coverage. In these areas, the resistance to erosive rainfall events is diminished. In a scenario of uncertainties of environmental policies concerning deforestation, this area could be compromised by soil erosion. The maintenance of protective coverage and implementation of conservation practices are fundamental to preserve soil quality. Ferralsols is the soil group less susceptible to erosion. However, they become very vulnerable under intensive tillage and demand the application of soil conservation practices.

Data availability

The dataset is freely available at https://doi.org/10.5281/zenodo.4279869

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Appendices

Appendix 1 – Figure S1. Sand, silt, and clay content for each soil group

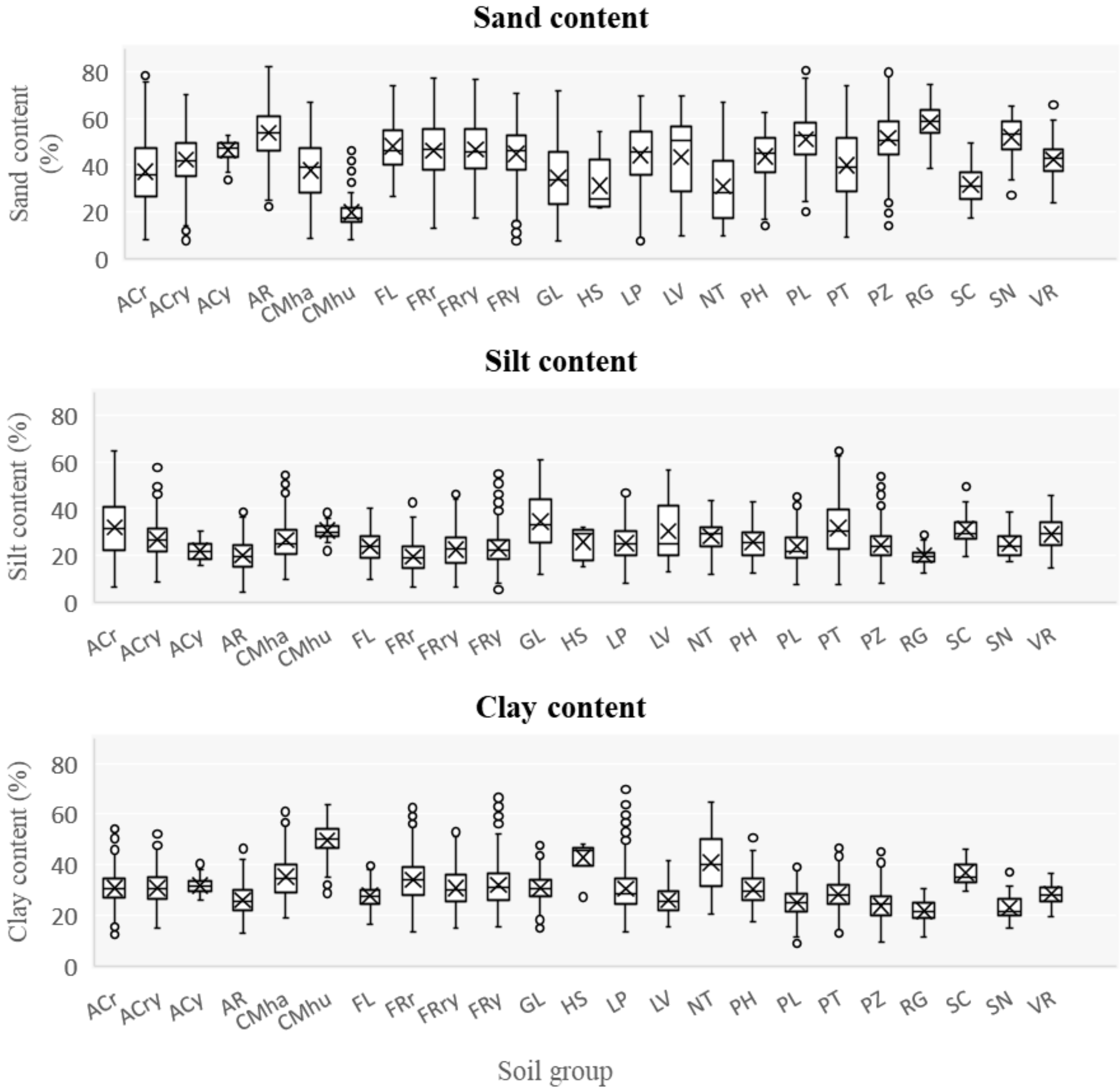

Fig. S1. Sand, silt, and clay content for each soil group. Box = 25th and 75th percentiles; line in the middle of the box = median; x = mean; bars = min and max values; points = outliers; ACry – Acrisol (red yellow); ACr – Acrisol (red); ACy – Acrisol (yellow); AR – Arenosol; CMha – Cambisol (haplic); CMhu – Cambisol (humic); FL – Fluvisol; FRry – Ferralsol (red yellow); FRr – Ferralsol (red); FRy – Ferralsol (yellow); GL – Gleysol; HS – Histosol; LP – Leptosol; LV – Luvisol; NT – Nitisol; PH – Phaeozem; PL – Planosol; PT – Plinthosol; PZ – Podzol; RG – Regosol; SC – Solonchak; SN – Solonetz; VR – Vertisol.

Appendix 2 – Table S1. Compiled data of soil erodibility field determination

Table S1. Compiled data of soil erodibility field determination.

Soil Type	K-factor (ton h $MJ^{-1} mm^{-1}$)	Method of rain	Time (years)	Region	Local	Source
Ferralsol (red)	0.0117	NR	5.0	CO	Dourados, MS	[9]
Ferralsol (red)	0.0130	NR	6.0		Planaltina, DF	[5]
Ferralsol (red)	0.0045	NR	23.0		Dourados, MS	[16]
Ferralsol (red)	0.0090	NR	5.0		Goiânia, GO	[30]
Ferralsol (red)	0.0020	SR	x		Ceres, GO	[22]
Ferralsol (red)	0.0030	SR	x		Ceres, GO	[22]
Nitisol	0.0210	SR	x		Ceres, GO	[22]
Nitisol	0.0210	SR	x		Ceres, GO	[22]
Nitisol	0.0210	SR	x		Ceres, GO	[22]
Ferralsol (yellow)	0.0110	NR	3.0	N	Manaus, AM	[30]
Ferralsol (yellow)	0.0090	NR	-		Tomé Açu, PA	[30]
Luvisol	0.0130	NR	7.0	NE	Sumé, PB	[1]
Acrisol (red yellow)	0.0140	NR	5.0		Glória do Goitá, PE	[7]
Acrisol (red yellow)	0.0154	NR	-		Serra Talhada, PE	[18]
Acrisol (red yellow)	0.0100	NR	5.0		Glória do Goitá, PE	[4]
Leptosol	0.0350	NR	0.5		Sobral, CE	[26]
Acrisol (red yellow)	0.0180	SR	x		CE	[18]
Acrisol (red yellow)	0.0220	SR	x		Serra Talhada, PE	[18]
Acrisol (red)	0.0310	SR	x		Alagoa Nova, PB	[27]
Acrisol (red)	0.0180	SR	x		Itapororoca, PB	[27]
Acrisol (red yellow)	0.0320	SR	x		Alagoa Grande, PB	[27]
Luvisol	0.0320	SR	x		Gurinhém, PB	[27]
Leptosol	0.0050	SR	x		PB	[1]
Leptosol	0.0080	SR	x		PB	[1]
Acrisol (red)	0.0080	SR	x		Teixeira, PB	[27]
Acrisol (red yellow)	0.0250	SR	x		Tavares, PB	[27]
Luvisol	0.0080	SR	x		Patos, PB	[27]
Ferralsol (red yellow)	0.0020	SR	x		Areia, PB	[30]
Ferralsol (red yellow)	0.0340	SR	x		Ubajara, CE	[30]
Luvisol	0.0090	-	-		Casserengue, PB	[20]
Acrisol (red)	0.0040	-	-		Patos, PB	[20]
Solonetz	0.0120	-	-		Boa Vista, PB	[20]
Acrisol (yellow)	0.0450	-	-		Fortaleza, CE	[20]
Acrisol (red yellow)	0.0080	-	-		Quixadá, CE	[20]

Cambisol (humic)	0.0180	NR	2.9	S	Lages, SC	[3]
Ferralsol (red)	0.0320	NR	4.0		Londrina, PR	[4]
Cambisol (humic)	0.0151	NR	8.0		Lages, SC	[5]
Ferralsol (red)	0.0212	NR	8.9		Chapecó, SC	[5]
Ferralsol (red)	0.0220	NR	3.0		Ponta Grossa, PR	[17]
Acrisol (red yellow)	0.0338	NR	13.0		Eldorado do Sul, RS	[10]
Ferralsol (red)	0.0091	NR	1.4		Santo Ângelo, RS	[11]
Ferralsol (red)	0.0090	NR	-		Ijuí, RS	[30]
Ferralsol (red)	0.0210	NR	-		Passo Fundo, RS	[30]
Nitisol	0.0330	NR	3.0		Guaíba, RS	[4]
Nitisol	0.0163	NR	0.8		Maringá, PR	[14]
Acrisol (red yellow)	0.0260	NR	3.0		Bela Vista do Paraíso, PR	[4]
Ferralsol (red)	0.0038	NR	7.0		Paranavaí, PR	[17]
Ferralsol (red)	0.0037	NR	15.0		Ponta Grossa, PR	[17]
Acrisol (yellow)	0.0004	NR	6.5		Aracruz, ES	[23]
Acrisol (yellow)	0.0070	NR	6.5		Aracruz, ES	[23]
Plinthosol	0.0170	NR	6.5		Aracruz, ES	[23]
Ferralsol (red)	0.0094	NR	1.0		Paranavaí, PR	[4]
Cambisol (humic)	0.0175	NR	20.0		Lages, SC	[28]
Ferralsol (red)	0.0160	NR	-		Chapecó, SC	[30]
Acrisol (red)	0.0026	NR	5.2		Eldorado do Sul, RS	[33]
Ferralsol (red)	0.0078	NR	3.0		Ijuí, RS	[4]
Ferralsol (red)	0.0200	NR	1.0		Passo Fundo, RS	[4]
Acrisol (red yellow)	0.0330	NR	4.3		Santa Maria, RS	[2]
Nitisol	0.0110	SR	x		São José do Cerrito, SC	[6]
Nitisol	0.0220	SR	x		Guaíba, RS	[4]
Nitisol	0.0310	SR	x		Guaíba, RS	[4]
Acrisol (red)	0.0240	SR	x		Santa Maria, RS	[27]
Ferralsol (red)	0.0250	SR	x		Londrina, PR	[30]
Ferralsol (red)	0.0072	SR	x		Paranavaí, PR	[4]
Ferralsol (red)	0.0210	SR	x		Passo Fundo, RS	[4]
Acrisol (red yellow)	0.0040	-	-		Morretes, PR	[20]
Acrisol (red)	0.0340	-	-		Eldorado do Sul, RS	[20]
Acrisol (red)	0.0320	-	-		Santa Maria, RS	[20]
Ferralsol (red)	0.0122	NR	3.0	SE	Campinas, SP	[4]
Ferralsol (red)	0.0120	NR	21.0		Campinas, SP	[30]
Nitisol	0.0232	NR	19.0		Mococa, SP	[8]

Acrisol (red yellow)	0.0044	NR	7.0		Pindorama, SP	[15]
Ferralsol (red)	0.0101	NR	7.0		Campinas, SP	[15]
Ferralsol (red)	0.0120	NR	39.0		Campinas, SP	[12]
Acrisol (red yellow)	0.0090	NR	5.0		Seropédica, RJ	[13]
Acrisol (red)	0.0330	NR	2.8		Sete Lagoas, MG	[21]
Ferralsol (red)	0.0020	NR	2.8		Sete Lagoas, MG	[21]
Cambisol (haplic)	0.0355	NR	4.9		Lavras, MG	[31]
Ferralsol (red)	0.0032	NR	4.9		Lavras, MG	[31]
Ferralsol (red)	0.0001	NR	3.9		Guanhães, MG	[32]
Ferralsol (red yellow)	0.0002	NR	3.9		Belo Oriente, MG	[32]
Ferralsol (red)	0.0090	SR	x		Jaboticabal, SP	[30]
Acrisol (red yellow)	0.0390	SR	x		Catanduva, SP	[24]
Acrisol (red yellow)	0.0230	SR	x		Catanduva, SP	[24]
Acrisol (red yellow)	0.0088	SR	x		Viçosa, MG	[4]
Acrisol (red yellow)	0.0270	SR	x		Viçosa, MG	[27]
Ferralsol (red)	0.0040	SR	x		Lavras, MG	[29]
Ferralsol (red yellow)	0.0100	SR	x		Lavras, MG	[29]
Acrisol (red)	0.0040	-	-		Pindorama, SP	[20]
Acrisol (red yellow)	0.0330	-	-	-	-	[19]
Ferralsol (red yellow)	0.0220	-	-	-	-	[19]
Acrisol (red)	0.0320	-	-	-	-	[25]

NR – natural rainfall; SR – simulated rainfall. AC – Acre, AM – Amazonas, RR – Roraima, RO – Rondônia, AP – Amapá, PA – Pará, MT – Mato Grosso, MS – Mato Grosso do Sul, TO – Tocantis, MA – Maranhão, GO – Goiás, PI – Piauí, CE – Ceará, RN – Rio Grande do Norte, PB – Paraíba, PE – Pernambuco, AL – Alagoas, SE – Sergipe, BA – Bahia, MG – Minas Gerais, ES – Espírito Santo, RJ – Rio de Janeiro, SP – São Paulo, PR – Paraná, SC – Santa Catarina; and RS – Rio Grande do Sul.

Appendix 3 – Table S2. Summary of compiled data of soil erodibility field determination

Table S2. Summary of compiled data of soil erodibility field determination.

Soil type	Rain method	Count of samples						Total count	Mean K-factor
		Region							
		CO	N	NE	S	SE	Unknown		
Acrisol (red yellow)				**8**	**4**	**6**	**1**	**19**	**0.0203**
	NR			3	3	2		8	0.0182
	SR			4		4		8	0.0244
	unknown			1	1		1	3	0.0150
Acrisol (red)				**4**	**4**	**2**	**1**	**11**	**0.0202**
	NR				1	1		2	0.0178
	SR			3	1			4	0.0203
	unknown			1	2	1	1	5	0.0212
Acrisol (yellow)				**1**	**2**			**3**	**0.0175**
	NR				2			2	0.0037
	unknown			1				1	0.0450
Cambisol (haplic)						**1**		**1**	**0.0355**
	NR					1		1	0.0355
Cambisol (humic)					**3**			**3**	**0.0169**
	NR				3			3	0.0169
Ferralsol (red yellow)				**2**		**2**	**1**	**5**	**0.0136**
	NR					1		1	0.0002
	SR			2		1		3	0.0153
	unknown						1	1	0.0220
Ferralsol (red)		**6**			**15**	**9**		**30**	**0.0112**
	NR	4			12	7		23	0.0115
	SR	2			3	2		7	0.0102
Ferralsol (yellow)			**2**					**2**	**0.0100**
	NR		2					2	0.0100

Leptosol				**3**				**3**	**0.0160**
	NR			1				1	0.0350
	SR			2				2	0.0065
Luvisol				**4**				**4**	**0.0155**
	NR			1				1	0.0130
	SR			2				2	0.0200
	unknown			1				1	0.0090
Nitisol		**3**			**5**	**1**		**9**	**0.0222**
	NR				2	1		3	0.0242
	SR	3			3			6	0.0212
Plinthosol					**1**			**1**	**0.0170**
	NR				1			1	0.0170
Solonetz				**1**				**1**	**0.0120**
	unknown			1				1	0.0120
Total count		9	2	23	34	21	3	**92**	

NR – natural rainfall; SR – simulated rainfall. CO – central-west; N – north; NE – northeast; SE – southeast; and S – South.

Appendix 4 – Table S3. Percent errors of estimated K-factor values

Table S3. Percent errors of estimated K-factor values.

Soil Type	Rain method	K_{obs}	USLE Nomograph K_{nomo}	USLE Nomograph Relative Error (%)	EPIC K_{EPIC}	EPIC Relative Error (%)
Acrisol (red yellow)		**0.0203**	0.0179	**11.5%**	0.0311	**53.2%**
	NR	0.0182		1.4%		70.8%
	SR	0.0244		26.3%		27.6%
	Unknown	0.0150		19.7%		107.2%
Acrisol (red)		**0.0202**	0.0201	**0.8%**	0.0329	**62.4%**
	NR	0.0178		12.8%		84.6%
	SR	0.0203		0.8%		62.3%
	Unknown	0.0212		5.3%		55.0%
Acrisol (yellow)		**0.0175**	0.0146	**16.4%**	0.0290	**66.2%**
	NR	0.0037		294.8%		684.7%
	Unknown	0.0450		67.5%		35.5%
Cambisol (haplic)		**0.0355**	0.0264	**25.5%**	0.0311	**12.5%**
	NR	0.0355		25.5%		12.5%
Cambisol (humic)		**0.0169**	0.0260	**54.3%**	0.0331	**96.4%**
	NR	0.0169		54.3%		96.4%
Ferralsol (red yellow)		**0.0136**	0.0120	**11.7%**	0.0294	**115.3%**
	NR	0.0002		5920.0%		14582.0%
	SR	0.0153		21.5%		91.5%
	Unknown	0.0220		45.3%		33.5%
Ferralsol (red)		**0.0112**	0.0106	**5.1%**	0.0283	**152.6%**
	NR	0.0115		7.7%		145.7%
	SR	0.0102		4.2%		177.4%

Ferralsol (yellow)		**0.0100**	0.0121	**20.6%**	0.0295	**195.4%**
	NR	0.0100		20.6%		195.4%
Leptosol		**0.0160**	0.0217	**35.6%**	0.0307	**92.0%**
	NR	0.0350		38.0%		-12.2%
	SR	0.0065		233.7%		372.5%
Luvisol		**0.0155**	0.0247	**59.4%**	0.0327	**111.2%**
	NR	0.0130		90.1%		151.8%
	SR	0.0200		23.6%		63.7%
	Unknown	0.0090		174.6%		263.8%
Nitisol		**0.0222**	0.0261	**17.9%**	0.0319	**43.7%**
	NR	0.0242		8.2%		31.9%
	SR	0.0212		23.5%		50.5%
Plinthosol		**0.0170**	0.0202	**18.9%**	0.0329	**93.4%**
	NR	0.0170		18.9%		93.4%
Solonetz		**0.0120**	0.0230	**91.6%**	0.0307	**155.9%**
	Unknown	0.0120		91.6%		155.9%

NR – natural rainfall; SR – simulated rainfall.

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