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# APPLICATIONS OF THE REVISED UNIVERSAL SOIL LOSS EQUATION (RUSLE) AT NATIONAL AND SUBNATIONAL SCALES: A GLOBAL ASSESSMENT AND A PRACTICAL CASE STUDY IN BRAZIL


SUPERVISOR

Prof. Gian Franco Capra

CANDIDATE

Rafael Barroca Silva

CO-SUPERVISORS

Prof. Iraê Amaral Guerrini

Prof. Antonio Ganga


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**Applications of the Revised Universal Soil Loss Equation (RUSLE) at national and subnational scales: A global assessment and a practical case study in Brazil**

Rafael Barroca Silva

Department of Architecture, Design and Urban Planning

University of Sassari

Sassary, Italy

**Abstract.** Soil is a vital and non-renewable resource fundamental to ecosystem functioning, food security, and landscape stability. Water erosion represents one of the main threats to its conservation. Over the history of Soil Science, several models have been developed to estimate soil loss by erosion, among which the Revised Universal Soil Loss Equation (RUSLE) is one of the most widely applied. The model integrates five factors related to rainfall erosivity, topography, soil properties, land cover, and conservation practices, and advances in remote sensing and Geographic Information Systems (GIS) have enabled its application over large spatial extents. Within this framework, this work combines a systematic review of large-scale RUSLE applications with an empirical spatial assessment of soil erosion in Brazil. The systematic review synthesized studies applying RUSLE at national and subnational scales, resulting in a final dataset of 59 studies. The results indicate a high heterogeneity in soil loss estimates worldwide, ranging from less than 1 Mg $ha^{-1}$ $yr^{-1}$ to more than 200 Mg $ha^{-1}$ $yr^{-1}$. Rainfall erosivity (R factor) and the length–slope factor (LS) were identified as the main drivers of soil erosion, while land cover (C factor) also plays a relevant role. Additionally, RUSLE was applied to the Northeast and Southeast macroregions of Brazil using open-access data from satellite imagery, meteorological stations, and national sources. Spatial analyses at state and municipal levels show that most areas fall within low erosion classes; however, the Southeast concentrates a higher proportion of areas with elevated soil loss, associated with steeper terrain and urbanized regions, whereas low erosion rates in the Northeast are linked to flatter landscapes, greater vegetation cover, or lower rainfall.

**Keywords:** Soil conservation; Land Use and Land Cover; Environmental monitoring; Soil erosion modelling; RUSLE systematic review

**Abstract.** Il suolo è una risorsa vitale e non rinnovabile, fondamentale per il funzionamento degli ecosistemi, la sicurezza alimentare e la stabilità del paesaggio. L'erosione idrica rappresenta una delle principali minacce alla sua conservazione. Nel corso della storia della Scienza del Suolo sono stati sviluppati diversi modelli per stimare la perdita di suolo dovuta all'erosione, tra i quali la Revised Universal Soil Loss Equation (RUSLE) è uno dei più ampiamente applicati. Il modello integra cinque fattori relativi all'erosività delle precipitazioni, alla topografia, alle proprietà del suolo, alla copertura del suolo e alle pratiche di conservazione, e i progressi nel telerilevamento e nei Sistemi Informativi Geografici (GIS) ne hanno consentito l'applicazione su ampie scale spaziali. In questo contesto, il presente lavoro combina una revisione sistematica delle applicazioni della RUSLE su larga scala con una valutazione spaziale empirica dell'erosione del suolo in Brasile. La revisione sistematica ha sintetizzato studi che applicano la RUSLE a scale nazionali e subnazionali, risultando in un dataset finale di 59 studi. I risultati indicano un'elevata eterogeneità nelle stime di perdita di suolo a livello mondiale, con valori che variano da meno di 1 Mg ha$^{-1}$ anno$^{-1}$ a oltre 200 Mg ha$^{-1}$ anno$^{-1}$. L'erosività delle precipitazioni (fattore R) e il fattore lunghezza–pendenza (LS) sono stati identificati come i principali determinanti dell'erosione del suolo, mentre anche la copertura del suolo (fattore C) svolge un ruolo rilevante. Inoltre, la RUSLE è stata applicata alle macroregioni Nordest e Sudest del Brasile utilizzando dati ad accesso aperto provenienti da immagini satellitari, stazioni meteorologiche e fonti nazionali. Le analisi spaziali a livello statale e municipale mostrano che la maggior parte delle aree rientra in classi di bassa erosione; tuttavia, il Sudest concentra una maggiore proporzione di aree con perdita di suolo elevata, associata a terreni più ripidi e regioni urbanizzate, mentre i bassi tassi di erosione nel Nordest sono legati a paesaggi più pianeggianti, maggiore copertura vegetale o minori precipitazioni.

**Keywords:** Conservazione del suolo; Land Use and Land Cover; Monitoraggio ambientale; modellazione dell'erosione del suolo; Revisione sistematica RUSLE

**Resumo.** O solo é um recurso vital, não renovável, fundamental para o funcionamento dos ecossistemas, segurança alimentar e a estabilidade da paisagem. A erosão hídrica representa uma das principais ameaças à sua conservação. Ao longo da história da Ciência do Solo, diversos modelos foram desenvolvidos para estimar a perda de solo por erosão, entre os quais a Revised Universal Soil Loss Equation (RUSLE) é um dos mais amplamente utilizados. O modelo integra cinco fatores relacionados à erosividade da chuva, topografia, propriedades do solo, cobertura da terra e práticas de conservação, e os avanços no sensoriamento remoto e nos Sistemas de Informação Geográfica (SIG) têm permitido sua aplicação em grandes extensões espaciais. Nesse contexto, este trabalho combina uma revisão sistemática das aplicações da RUSLE em larga escala com uma avaliação espacial empírica da erosão do solo no Brasil. A revisão sistemática sintetizou estudos que aplicaram a RUSLE em escalas nacionais e subnacionais, resultando em um conjunto final de 59 estudos. Os resultados indicam uma elevada heterogeneidade nas estimativas de perda de solo em nível global, variando de menos de 1 Mg ha$^{-1}$ ano$^{-1}$ a mais de 200 Mg ha$^{-1}$ ano$^{-1}$. A erosividade da chuva (fator R) e o fator comprimento–declividade (LS) foram identificados como os principais determinantes da erosão do solo, enquanto a cobertura do solo (fator C) também desempenha um papel relevante. Adicionalmente, a RUSLE foi aplicada às regiões Nordeste e Sudeste do Brasil, utilizando dados de acesso aberto provenientes de imagens de satélite, estações meteorológicas e fontes nacionais. As análises espaciais em nível estadual e municipal mostram que a maior parte das áreas se enquadra em classes de baixa erosão; no entanto, o Sudeste concentra uma maior proporção de áreas com perda de solo elevada, associada a terrenos mais íngremes e

regiões urbanizadas, enquanto as baixas taxas de erosão no Nordeste estão relacionadas a paisagens mais planas, maior cobertura vegetal ou menores índices pluviométricos.
**Palavras-chave:** Conservação do solo; Land Uso and Land Cover; Monitoramento ambiental; Modelagem da erosão do solo; Revisão sistemática da RUSLE

## PREFACE

I recall that at the beginning of my PhD program in Architecture and Environment, during one of the first classes, a professor presented the following line of reasoning: "*Data* is transformed into *information* by adding context, organization, and structure; *information* is transformed into *knowledge* through interpretation, analysis, and synthesis; and *knowledge* is transformed into *Wisdom* through reflection, experience, and decision-making." At that moment, I realized that, ultimately, the true goal of science is to produce wisdom. All the work we do, often without reflection or introspection, like automatons, would otherwise be in vain. Doing science, whether as a student, researcher, or in any other role, requires calm and deep reflection, even though it often slips through our fingers like sand.

I was in Sardinia when Professors Capra and Ganga presented the initial question about applying the Revised Universal Soil Loss Equation (RUSLE) to the Northeast and Southeast regions of Brazil. Together with Professor Guerrini and colleagues Paganini, Roder, and Justino, we continued studying and refining the nuances of the research until it became the central topic of this thesis. As the ideas matured, we included a further research question: what is the state of the art in the application of RUSLE at national and subnational scales, that is, within political-administrative boundaries? Therefore, this volume contains two chapters: the first aims to answers this question, and the second presents the results of applying the model to the two Brazilian regions.

Soil is a fundamental resource for the Earth ecosystems, and as humanity, we still fail to grasp the seriousness of the damage caused by practices that promote soil loss. In most cases, inadequate agricultural and engineering techniques cause soil losses at rates greater than those of soil formation, which occurs very slowly. Hence the importance of models that estimate soil loss. Among them, RUSLE remains one of the most classical, simple, functional, and educational tools for this purpose.

Certainly, this thesis does not exhaust the subject, but I hope it offers knowledge, synthesis, interpretation, and helps to increase – even if only a little – the Wisdom with which we relate to the soil.

## PREFAZIONE

Ricordo bene quando iniziai il percorso di Dottorato in Architettura e Ambiente, nel fine 2022. In una delle prime lezioni, un professore presentò il seguente ragionamento: «*Data* is transformed into *information* by adding context, organization and structure; *information* is transformed into *knowledge* through interpretation, analysis and synthesis; and *knowledge* is transformed into *Wisdom* through reflection, experience and decision-make» In quel momento capii che, in fondo, l'obiettivo della Scienza è produrre Saggezza. Altrimenti, tutto il lavoro che svolgiamo, spesso senza riflessione né introspezione, come automi, sarebbe vano. Fare Scienza, sia come studente, ricercatore o in qualsiasi altra posizione, richiede calma e molta riflessione, anche se spesso ci sfugge tra le dita come sabbia.

Mi trovavo in Sardegna quando i professori Capra e Ganga mi presentarono la domanda iniziale sull'applicazione della Revised Universal Soil Loss Equation (RUSLE) alle regioni Nordest e Sudest del Brasile. Insieme al professor Guerrini e ai colleghi Paganini, Roder e Justino, abbiamo continuato a studiare e perfezionare i dettagli della ricerca, fino a consolidarla come tema di questa tesi. Durante la maturazione delle idee, si è aggiunta un'ulteriore domanda di ricerca: qual è lo stato dell'arte dell'applicazione della RUSLE su scale nazionali e subnazionali, cioè all'interno dei confini politico-amministrativi? Pertanto, questo volume contiene due capitoli: il primo cerca di rispondere a questa domanda; il secondo presenta i risultati dell'applicazione del modello nelle due regioni del Brasile.

Il suolo è una risorsa fondamentale per i diversi ecosistemi del pianeta, e noi, come umanità, non comprendiamo ancora la gravità delle azioni inadeguate che ne provocano la perdita. Quasi sempre, tecniche agricole o ingegneristiche inappropriate causano la perdita di suolo a tassi superiori a quelli della sua formazione, che avviene molto lentamente. Da qui l'importanza dei modelli di stima della perdita di suolo; tra essi, la RUSLE rimane uno dei più classici, semplici, funzionali e didattici.

Senza dubbio, questa tesi non esaurisce l'argomento, ma spero che porti almeno un po' di conoscenza, sintesi, interpretazione e contribuisca ad aumentare – anche solo minimamente – la saggezza con cui ci relazioniamo con il suolo.

# PREFÁCIO

Me recordo bem, de quando comecei o percurso do Doutorado em Arquitetura e Ambiente, que numa das aulas logo no início do curso, um professor postulou o seguinte raciocínio: "*Data* is transformed into *information* by adding context, organization and structure; *information* is transformed into *knowledge* through interpretation, analysis and synthesis; and *knowledge* is transformed into *Wisdom* through reflection, experience and decision-make". Naquele momento, percebi que, no final das contas, o objetivo da Ciência é produzir sabedoria. Seria, de fato, em vão, todo o trabalho que fazemos, muitas vezes, sem reflexão e introspecção, como autômatos; e que, fazer Ciência, seja na posição de estudante, pesquisador, ou qualquer outra, demanda calma e muita reflexão, muito embora isso nos escape como areia entre os dedos.

Estava na Sardenha quando me foi apresentado, pelos professores Capra e Ganga, essa pergunta sobre a aplicação da Revised Universal Soil Loss Equation (RUSLE) para as regiões Nordeste e Sudeste do Brasil. Seguimos, então, juntamente com o prof. Guerrini, e os caros colegas Paganini, Roder e Justino, estudando e aperfeiçoando as nuances dessa pesquisa, até que foi consolidada como tema desta presente tese. Durante esse amadurecimento das ideias, houve a inclusão de uma ulterior pergunta de pesquisa: qual é o estado-da-arte da aplicação da RUSLE para escalas nacionais e subnacionais, ou seja, dentro de fronteiras político-administrativas? Portanto, o presente volume tem dois capítulos: o primeiro procura responder essa pergunta; e o segundo traz os resultados de uma aplicação do modelo nas duas regiões do Brasil.

O solo é um recurso fundamental aos diversos ecossistemas do planeta, e nós, enquanto humanidade, ainda não compreendemos a gravidade de ações inadequadas que promovem a sua perda. Quase sempre, as técnicas inapropriadas de agricultura e engenharia promovem perdas de solo em taxas superiores àquelas de formação do solo, que ocorre de forma muito lenta. Daí a importância dos modelos de estimativa da previsão de perda de solo, dentre os quais a RUSLE permanece como um dos mais clássicos, simples, funcionais e didáticos para essa finalidade.

Sem dúvida alguma, esta tese não esgota o tema, mas espero que traga pelo menos algum conhecimento, síntese, interpretação, e contribua para aumentar, nem que seja apenas um pouquinho, a sabedoria com a qual nos relacionamos com o solo.

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## SUMMARY

# GENERAL INTRODUCTION

The word "erosion" came from the Latin "*erodere*", which means to gnaw away, to wear out (https://www.oed.com/dictionary/erosion_n?tl=true). Within the field of Earth Sciences, erosion mean the removal of particles that constitutes surfaces, commonly rocks and/or soil. Several agents cause erosion, such as the wind, rainfall and mass movement in steeper reliefs. Erosion have a key role on soil development, as it is a process of material removal and transportation to other lower surfaces.

Soil erosion is a fundamental agent in the morphology of terrains, mainly through two ways: (1) when the soil surface is removed, a dissection relief is formed, potentially giving rise to valleys and canyons if conditions allow for it. In the other hand, a (2) depositional surface is created when sediments carried from higher elevations are deposited in lower-lying areas (Hancock et al. 2017).

An example of the importance of soil erosion in soil development and landscape formation is the occurrence of very deep Ferralsols in hilly terrains. Ferralsols are typically associated with flat of gently sloping landforms. However, they are also found in highly undulating, hilly landscapes. In Brazil, Bócoli et al. (2021) investigated gneiss Ferralsols in hilly landscapes and found evidence that these soils were originally formed in flat landscapes. Over millennia, the terrain underwent erosion, resulting in hilly reliefs, while the soils retained the key characteristics of the Ferralsol order. Among the evidences, is the higher terrains of these regions being at the same elevation range, within a homogeneous hilly landscape. Erosional processes are also relevant for soils developed from sedimentary rocks, such as limestones and sandstones, many times in processes associated with several other factors (Hermann et al. 2022; Souza et al. 2025).

After the emergence of the first civilizations, human actions enabled a large increase in soil erosion rates, through techniques that caused increasing disturbances to the soil structure, exposing it to the action of erosive agents (Gao et al. 2018) Historical evidence shows ancient agriculture in Africa and other continents had to deal with soil erosion (Dotterweich 2013). Soil erosion rates in the Anthropocene are often many times greater than pre-civilization rates. For instance, in North America, a research conducted by Reusser et al. 2015 found a soil erosion rate 100 times higher during a peak of agricultural activity (in the late 19$^{th}$ century) in comparison to pre-European colonization period.

Since about 38% of the World's land area is covered by agriculture (Foley et al. 2011), these anthropic activities lead to accelerated soil erosion, as referring to the human-induced processes leading to higher soil erosion (Naipal et al. 2015). Several environmental, economic and social impacts arise from accelerated soil erosion. Firstly, the removal of soil itself represents the loss of a non-renewable resource, since thousands of years of complex processes are required to form a single soil layer (Stockmann et al. 2014). Furthermore, the carrying of soil minerals to water bodies can induce eutrophication processes, which alters the ecology of streams and rivers (Ekholm and Lehtoranta 2012). Also, suspended sediments influence the water turbidity (Kabir and Ahmari 2020), thus altering the passage of light and various ecological processes of aquatic and benthic ecosystems (Song et al. 2022; Sahoo and Anandhi 2023).

At the economic sphere, the soil erosion causes an agricultural production loss of ~ 34 million tons, with a global GPD loss of around U$$ 8 billion (Sartori et al. 2019). The social effects of soil erosion are most pronounced in the developing World, where soil conservation policies and good agricultural practices are often ineffective or even absent in developing countries (Ananda and Herath 2003; Teku and Derbib 2025). As a matter of fact, the perspectives of agricultural expansion in these regions highlights the potential for increasing soil erosion rates in the future (Borrelli et al. 2017).

Notwithstanding the connected history of humankind and the accelerated soil erosion, several figures in history have expressed concerns about soil loss due to erosion and agricultural practices that favor productivity, empirically, in texts and preserved archaeological evidence (Dotterweich 2013). However, it was only in the Modern Era that the science of soil erosion became more systematic, with the study of its characteristics, causes and impacts. Advances in Soil Science have led to ever-increasing concern about soil erosion and the prevention and mitigation of its effects, particularly since the 19th century (Brevik and Hartemink 2010; Minasny et al. 2020).

A benchmark of the science on soil erosion was the development of the Universal Soil Loss Equation (USLE), first published in a consistent form by Wischmeier and Smith, in the U.S. Agricultural Handbook n. 282 (1965). The model was intended to provide basis for predicting soil erosion by rainfall impact and thus helping the selection of best practices for each situation. The basis for the model were field experimentation since the early 20$^{th}$ century in several locations within the United States. Over time, the USLE has served as a reference for the development of other soil erosion models in various regions of the world (Laflen and Flanagan 2013). Examples include the EPIC (Erosion Productivity Impact Calculator) (Sharpley and Williams 1990), SOILOSS (Rosewell and Edwards 1988) and the MUSLE (Modified Universal Soil Loss Equation) (Williams 1975). In 1997, Renard et al. published a revised version of the USLE, called the Revised

Universal Soil Loss Equation (RUSLE) (Renard et al. 1997). The original USLE factors remained, with updates to their computation and application within the model. RUSLE quickly became widely used for empirical estimates of soil loss due to water erosion in various regions of the world, and across a variety of area sizes.

Today, there are dozens of soil erosions models available for the most variable conditions of pedological features, climates and land use systems (Borrelli et al. 2021). Nevertheless, RUSLE remains an important tool for predicting soil loss due to erosion both locally and over large areas. This thesis consists of two chapters, both involving the use of remote sensing and geographic information systems for data acquisition, treatment and calculation.

The first chapter proposes to systematically review the application of RUSLE in large areas, focusing on first and second degree administrative levels, that is, nations and subnational entities. To this end, a search was carried out for published research within the scope and then relevant data was collected to quantify metrics of the main results. The second chapter aims to apply the RUSLE to estimate soil loss due to water erosion in the Northeast and Southeast regions of Brazil, consisting of 13 states in its territory. Due to the large size of the study area, it is possible to delve deeper into the discussion of various aspects, such as the relief, climate, and biomes present in the studied territory.

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# FIRST CHAPTER

## The use of RUSLE (Revised Universal Soil Loss Equation) for national and subnational scales: a systematic review

**Abstract**. Water erosion is one of the greatest threats to the conservation of the soil, a vital non-renewable resource. Throughout the history of Soil Science, several models have been developed to estimate soil loss due to erosion processes. Among them is RUSLE (Revised Universal Soil Loss Equation), composed of the multiplication of five factors that reflect rainfall, relief, soil type, land cover, and the application of conservation practices. The advent of Remote Sensing and Geographic Information Systems has enabled the application of the model to large areas. This study aimed to systematically review publications that applied RUSLE to obtain estimates of soil loss over large areas, at national and subnational scales. Searches were conducted in a database of scientific publications, followed by filtering and screening to include only articles relevant to the study in the final collection. Data from the studies were collected to generate statistics to assess key trends and how soil loss estimates behave across different countries and continents. In total, 59 studies were assembled in the final collection, being 29 at national and supranational scales, 28 at subnational scale and 2 covering the global land surface. There is a high heterogeneity of estimated soil loss values, ranging from less than 1 Mg ha$^{-1}$ yr$^{-1}$ to more than 200 Mg ha$^{-1}$ yr$^{-1}$. The rainfall erosivity (R-factor) and the length-slope (LS) factor They are the most influential factors in soil erosion outcomes. However, the C-factor is also very relevant, with areas under low vegetation cover or bad management practices being more prone to soil erosion.

**Abstract**. L’erosione idrica del suolo rappresenta una delle maggiori minacce per la conservazione di questa risorsa vitale e non rinnovabile. Nel corso della storia della Scienza del Suolo, sono stati sviluppati diversi modelli per stimare la perdita di suolo dovuta ai processi erosivi. Tra questi è la RUSLE (*Revised Universal Soil Loss Equation*), costituita dalla moltiplicazione di cinque fattori che riflettono precipitazioni, rilievo, tipo di suolo, copertura del terreno e applicazione di pratiche di conservazione. L’avvento del Remote Sensing e dei Geographic Information Systems ha reso possibile l’applicazione del modello su vaste aree. Questo studio ha avuto come obiettivo la revisione sistematica delle pubblicazioni che hanno applicato la RUSLE per ottenere stime di perdita di suolo su larga scala, sia quella nazionale e subnazionale. Le ricerche sono state condotte in un database di pubblicazioni scientifiche, seguite da fasi di filtraggio e selezione per includere solo gli articoli pertinenti alla raccolta finale. I dati degli studi sono stati raccolti per generare statistiche volte a valutare le principali tendenze e il comportamento delle stime di perdita di suolo in diversi paesi e continenti. In totale, sono stati raccolti 59 studi nella raccolta finale, di cui 29 a scala nazionale e sovranazionale, 28 a scala subnazionale e 2 che coprono la superficie terrestre globale. C’è un'elevata eterogeneità nei valori stimati della perdita di suolo, che vanno da meno di 1 Mg ha$^{-1}$ anno$^{-1}$ a più di 200 Mg ha$^{-1}$ anno$^{-1}$. L'erosività delle precipitazioni (fattore R) e il fattore lunghezza-pendenza (LS) sono i fattori più influenti sugli esiti dell'erosione del suolo. Tuttavia, anche il fattore C è molto rilevante, con aree con scarsa copertura vegetale o cattive pratiche di gestione che sono più soggette all'erosione del suolo.

**Resumo**. A erosão hídrica é uma das maiores ameaças à conservação do solo, um recurso vital e não renovável. Ao longo da história da Ciência do Solo, diversos modelos foram desenvolvidos para estimar a perda de solo decorrente dos processos erosivos. Entre eles está a RUSLE (*Revised Universal Soil Loss Equation*), composta pela multiplicação de cinco fatores que refletem a precipitação, o relevo, o tipo de solo, a cobertura do terreno e a aplicação de práticas conservacionistas. O advento do Sensoriamento Remoto e dos Sistemas de Informação Geográfica possibilitou a aplicação do modelo em grandes áreas. Este estudo teve como objetivo revisar sistematicamente as publicações que aplicaram a RUSLE para obter estimativas de perda de solo em grandes áreas, em escalas nacional e subnacional. As buscas foram realizadas em uma base de dados de publicações científicas, seguidas de etapas de filtragem e triagem para incluir apenas artigos relevantes à coleção final. Os dados dos estudos foram coletados para gerar estatísticas que permitissem avaliar as principais tendências e o comportamento das estimativas de perda de solo em diferentes países e continentes. No total, 59 estudos foram reunidos na coleção final, sendo 29 em escala nacional e supranacional, 28 em escala subnacional e 2 abrangendo a superfície terrestre global. Há uma grande heterogeneidade nos valores estimados de perda de solo, variando de menos de 1 Mg $ha^{-1}$ $ano^{-1}$ a mais de 200 Mg $ha^{-1}$ $ano^{-1}$. A erosividade da chuva (fator R) e o fator lenght-slope (LS) são os fatores que mais influenciam os resultados da erosão do solo. No entanto, o fator C também é muito relevante, sendo as áreas com baixa cobertura vegetal ou práticas de manejo inadequadas mais propensas à erosão do solo.

### 2.1 Introduction

Soil is a fundamental resource for sustaining human societies, due to its essential role in agriculture, livestock production, and civil construction. Furthermore, soil is a key component in various terrestrial natural ecosystems, ranging from the frosty tundra to hot savannas and tropical rainforests. The primary origin of soil is the weathering of rocks, which through chemical and physical processes, as well as biological activity, breaks them down into increasingly smaller fragments and particles until the formation of primary and secondary minerals that compose the soil's mineral phase. These particles are classified by modern Soil Science as sand, silt, and clay. Other processes, such as the deposition and sedimentation of particles transported by wind or water, are also important for shaping a soil profile (Zádorová et al., 2025).

Soil formation is an extremely slow process, with rates varying across colder and warmer regions of the planet (Stockmann et al., 2014). Due to the long timescales required for its development, soil is considered a non-renewable natural resource. Water erosion of soils can occur naturally or be induced by human activities. Natural soil erosion is a key process in shaping landforms and landscapes (Doe & Harmon, 2001; Dosseto et al., 2011), through the removal of material from higher areas and its subsequent transport and deposition in lower areas, thereby controlling the morphology of slopes, valleys, and depositional surfaces (Carey et al., 2024). However, since ancient times, soil erosion has been significantly influenced by agriculture and livestock grazing, becoming progressively more intense as agricultural techniques evolved throughout history (Dotterweich, 2013; dos Santos et al., 2023). In some parts of the world, particularly where agriculture has been highly intensified, soil erosion rates are often many times greater than natural rates (Reusser et al., 2015; Nearing et al., 2017). For this reason, Soil Science is deeply engaged in studying ways to prevent and mitigate water erosion, focusing on understanding its causes, dynamics, and processes, as well as developing soil conservation and agricultural management practices.

One approach to studying soil erosion is the prediction and estimation of its intensity and impacts through models and algorithms. Examples include the USLE (Universal Soil Loss Equation), MUSLE (Modified Universal Soil Loss Equation), and EPIC (Erosion Productivity Impact Calculator) (Laflen & Flanagen, 2013). One of the most widely used models to predict soil loss from water erosion is the RUSLE (Revised Universal Soil Loss Equation), which maintains the original USLE structure while improving the computation and estimation of its factors (Renard et al. 1997).

In recent decades, advances in remote sensing technologies and computational tools have enabled the calculation of RUSLE factors over areas much larger than small-scale study sites. RUSLE has been applied in watersheds, ecological zones, municipalities, and other areas of interest. Thanks to modern tools, it can now be applied on national, continental, and even global scales. Applying RUSLE to large areas allows the generation of valuable information for identifying regions most susceptible to water erosion and, consequently, for predicting its economic, environmental, and social impacts (Fadl et al., 2025). Furthermore, such information is essential for the design and planning of soil conservation practices and policies.

This study aims to perform a comprehensive systematic review of publications that have applied the RUSLE model to large spatial extents, encompassing national and subnational scales. In addition, it seeks to compile and analyze relevant data to generate statistical insights, enabling the identification of patterns, trends, and key characteristics of the results reported in these studies. Such an approach is intended to provide a broader understanding of how RUSLE has been employed in large-scale contexts and to support the advancement of erosion modeling and soil conservation strategies.

## 2.2 Methodology

### *2.2.1 Collection and handling of literature material*

The first step of the review was the search and collection of literature material. The main subject were research papers that deal with the soil loss estimation by using the RUSLE model, for different areas. At a first step, the Scopus database was used to search for the collection of papers. Two searches were done, each one with a setting of keywords in the "title, abstract and keywords" category: (1) "RUSLE" *AND* "soil loss" *AND* "water erosion"; and (2) "RUSLE" *AND* "large scale". The second search was conducted to ensure the inclusion of articles that clearly addressed the application of RUSLE in large areas. Still on the Scopus platform, search results were filtered according to the following criteria:

(a) Only research articles (thus excluding review articles, conference papers, editorials, encyclopedia and newspapers);

(b) Only in English language;

(c) Only publications in peer-reviewed journals (thus excluding articles from other publication types);

(d) Exclusion criteria: research papers under the following subject areas: Arts and humanities; Business, management and accounting; Health; Immunology and microbiology; Materials Science; Medicine; Pharmacology; Toxicology and Pharmaceutics; Veterinary Science and Veterinary Medicine.

The results of the searches were merged within a collection in the Rayyan program (Ouzzani et al., 2016) for downstream handling. The following step was the identification and management of duplicate articles. All duplicates with 100% of similarity were excluded from the collection. A response article was also found, and then was excluded too.

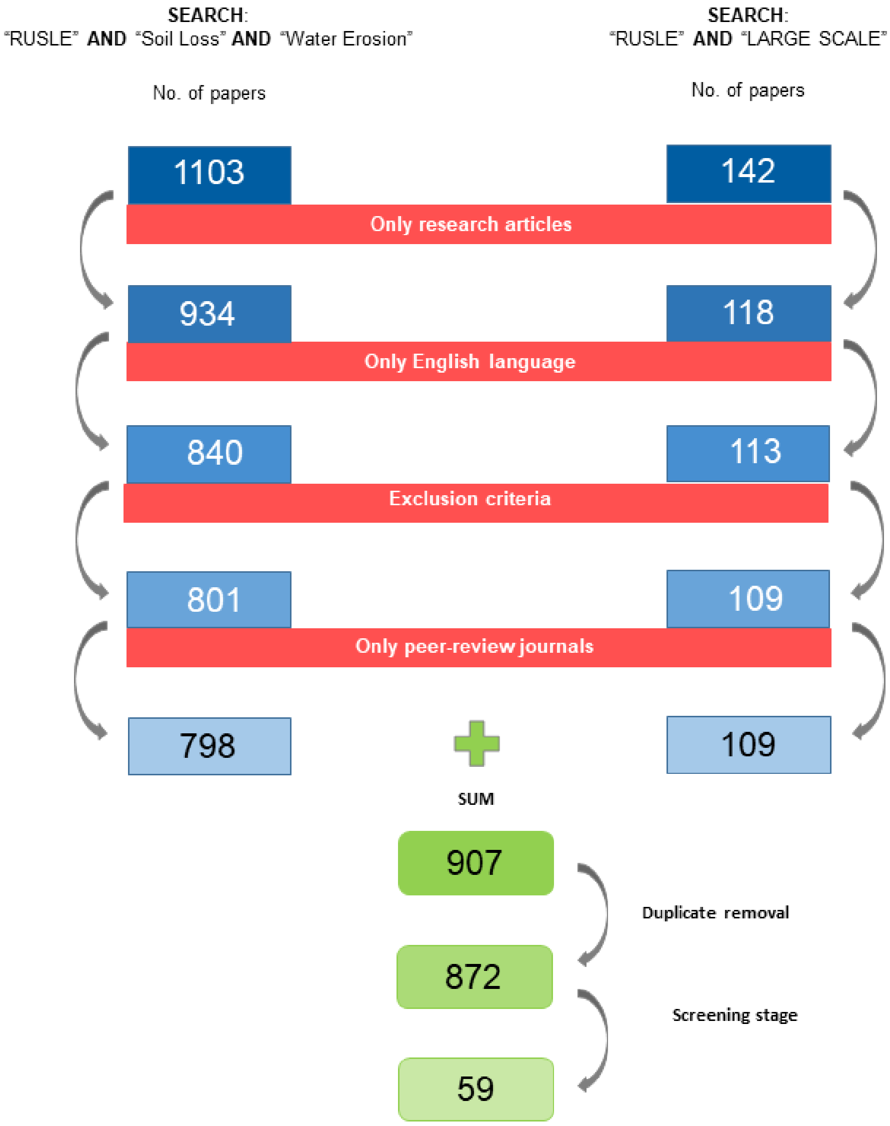
After the duplicates removal, the articles were screened under inclusion and exclusion criteria. The first approach was to search for specific keywords within the article's abstracts. The selection of inclusion keywords was done based on words suggesting administrative boundaries. The final selection was "continent; continental; country; macro scale; national; nationwide; province; region; regional; state". The criteria for exclusion were defined on keywords that suggest smaller areas, such as river and creek basin, municipalities, etc. The final selection was "basin; catchment; drainage basin; municipality; river basin; watershed". This process was made with a filter tool within the Rayyan program (table 1).

**Table 1 – Number of publications labelled with each inclusion and exclusion keywords.**

| Inclusion keywords | No. of publications | Exclusion keywords | No. of publications |
|---|---|---|---|
| Continent | 03 | Basin | 262 |
| Continental | 10 | Catchment | 118 |
| Country | 37 | Drainage basin | 4 |
| Macro scale | 1 | Municipality | 6 |
| National | 52 | River basin | 109 |
| Nationwide | 4 | Watershed | 309 |
| Province | 39 | | |
| Region | 220 | | |
| Regional | 107 | | |
| State | 54 | | |

The labeling was applied to facilitate the screening stage. In this stage, each title and abstract were carefully reviewed for information that would allow its inclusion or exclusion from the final list. As the final objective was a collection of publications that provided soil erosion estimates using RUSLE with remote sensing, those works that did not include this requirement were removed. Only publications that clearly applied RUSLE at the administrative scale, at national or subnational levels, were included. Publications that applied RUSLE at the continental scale were also admitted. A time limit was also applied, with articles published from 2015 to the present being included in the final collection. This temporal limitation was adopted to ensure greater methodological consistency across the selected studies, given the rapid evolution of data availability, computational capacity, and analytical techniques in environmental and geospatial research.

**Figure 1 – Pipeline of the search operation within the Scope database, followed by the duplicate removal and screening stages within the Rayyan software.**


SEARCH:
"RUSLE" AND "Soil Loss" AND "Water Erosion"
No. of papers
SEARCH:
"RUSLE" AND "LARGE SCALE"
No. of papers
1103
142
Only research articles
934
118
Only English language
840
113
Exclusion criteria
801
109
Only peer-review journals
798
109
SUM
907
Duplicate removal
872
Screening stage
59

### *2.2.2 Analysis of the collected articles: data collection*

The research articles within the final collection were searched to extract data covering the following subjects:

(a) Study area: area (km²), location, delimitation (natural or political boundaries);

(b) Other methods for soil loss estimation (in addition to RUSLE);

(c) Methods for obtaining the RUSLE factors (*what approach were used for each factor?*);

(d) Average result of soil loss by RUSLE;

(e) Suggested main factor driving the soil erosion (if the text suggest it in any section).

These results were assembled in an Excel database for posterior analysis within the R Studio IDE from the R analysis environment (R Core Team, 2021; Posit Team 2025).
Some works were also excluded because, even spatialized the erosion within a territory, did not used the RUSLE as the main tool (examples: Jelinski & Yoo, 2016).
After the assembling of the final collection, the publications were classified into three categories:

1) Studies that applied RUSLE at national or supranational scales, such as China, Morocco, European Union;
2) Studies that applied RUSLE at subnational scales, such as Basilicata (Region of Italy), Henan (Province in Central China).

### *2.2.4 Statistical analysis*

For data interpretation, descriptive statistics were used. The calculated statistics for soil loss estimates included the mean, median, standard deviation, coefficient of variation, and maximum and minimum values. It is important to emphasize that soil erosion data generated using RUSLE tend to show a pronounced left skew due to the inherent characteristics of the model's factors. In most areas where RUSLE is applied, the majority of the territory exhibits low erosion, while only a few zones show high erosion, except in regions where the terrain is steep or highly rugged across large portions of the area.

For visualization of number of papers by continent and countries, the treemapping technique was applied, by using the function treemap() of the "treemap" package for R (Tennekes, 2023).

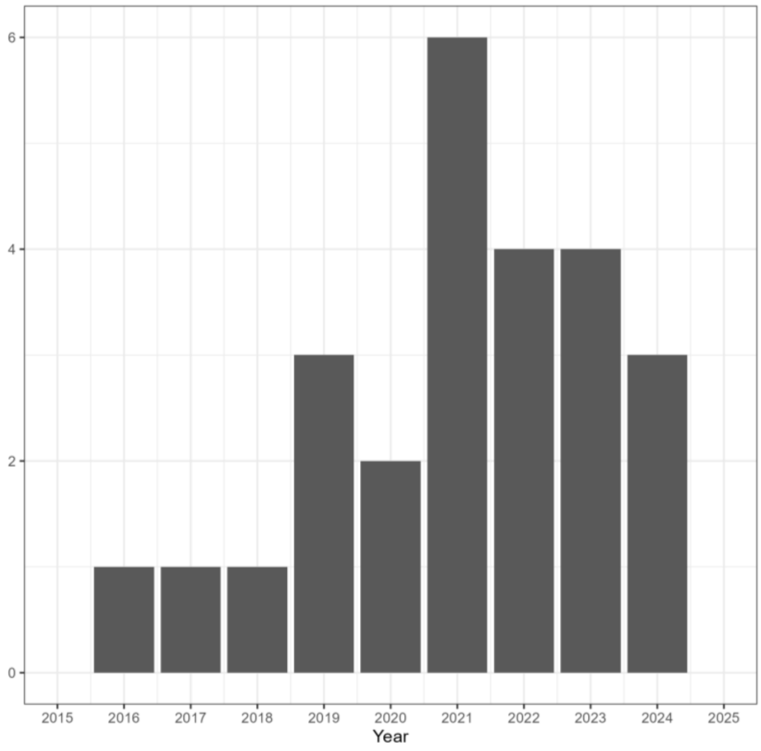
### 2.3 Results

After removing duplicates, filtering by keywords, and screening the publications one by one, the final collection was assembled. The final list included 59 publications. Of these, 29 presented the RUSLE model applied at the national or supranational scale, that is, they estimated soil loss at the country or country grouping levels. Another 28 studies applied the equation at the first-order subnational scale, i.e., states, provinces, etc. Only two studies assessed soil loss on a global scale, applying the RUSLE model to the entire Earth's land surface.

#### *2.3.1 Studies applying RUSLE at national and supranational scales*

Within the last decade, the highest number of studies were published from 2021 to 2023, with four or more papers published per year (Figure 2). The years with the fewest publications were 2016 to 2018, with only one article each.

**Figure 2 – Number of publications by year (2015-2025).**

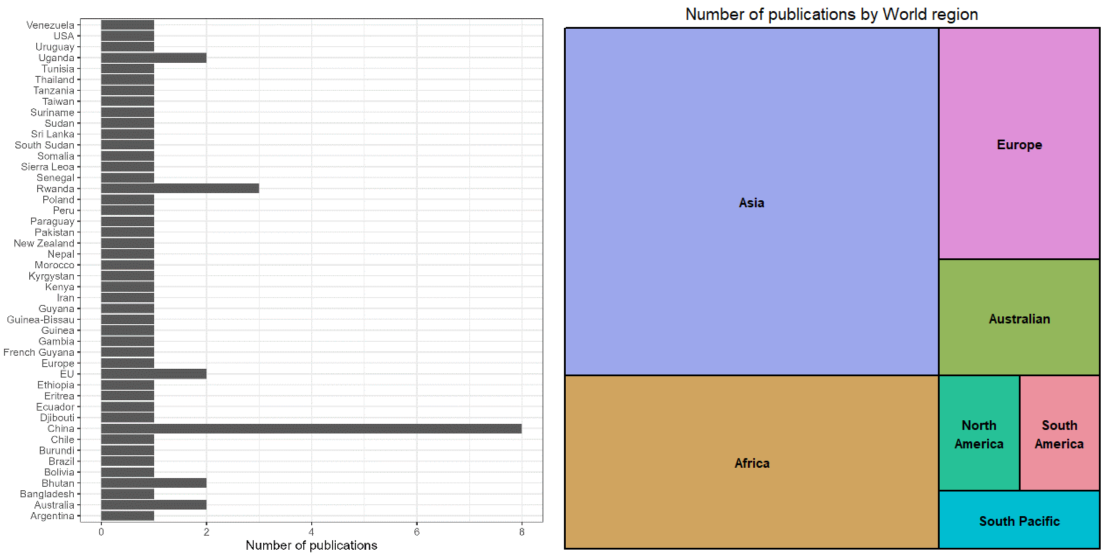



Asia was the continent with the highest number of publications, contributing 14 studies applying RUSLE on a national scale. Eight of these studies were applied to the territory of China, the nation with the most number of researches. Other Asian countries that were the subject of study included Iran in West Asia, Pakistan, Nepal and Bangladesh in South Asia, Kyrgyz Republic in Central Asia and Taiwan in East Asia.

The African continent had the second highest number of studies, with 7 publications applying RUSLE in 18 countries. In West Africa, Guinea, Guinea-Bissau, and Sierra Leone were studied, while in East Africa, countries such as Eritrea, Ethiopia, Kenya, Somalia, and Sudan were included. In North Africa, Morocco and Tunisia were studied.

The continent with the third highest number of studies was Europe, with 3 publications. Two of these studies covered the entire territory of the European Union, meaning they are supranational in scale, covering an area of over 4 million square kilometers and 27 member states. One study studied the soil erosion in Poland.

**Figure 3 – Number of publications (RUSLE applied at national or supranational scale) by country and World region.**




The Australian continent has two studies, both applying RUSLE to Australian territory. North and South America each had one publication, with estimates of soil loss for the USA and all South American countries, respectively.

The country with the largest land area included in the studies was China, in East Asia, with over 9.5 million square kilometers, while the smallest area was Gambia, in West Africa, with 11,300 km$^2$.

**Table 2 – Distribution of researches that applied RUSLE at national and supranational scale by continent and nation.**

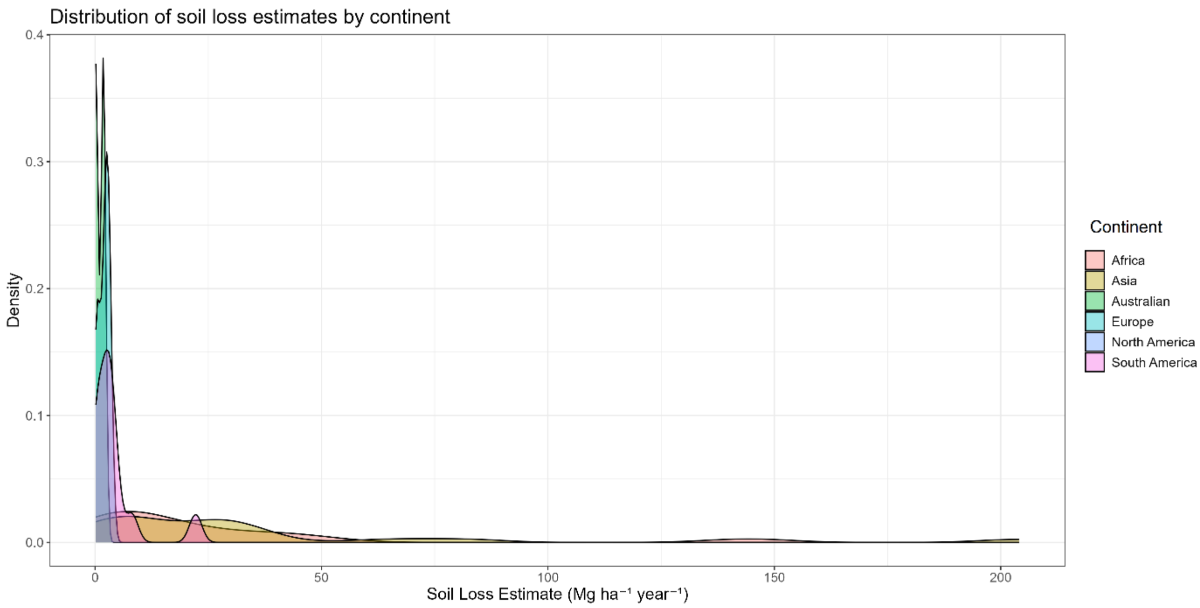
| Continent or World Region | No. | Nation |
|---|---|---|
| Africa | 7 | Burundi, Djibouti, Eritrea, Ethiopia, Gambia, Guinea-Bissau, Kenya, Morocco, Rwanda (3), Senegal, Sierra Leoa, Somalia, South Sudan, Sudan, Tanzania, Tunisia, Uganda (2) |

| | | |
|---|---|---|
| Asia | 14 | Bangladesh, Bhutan (2), China (8), Iran, Kyrgyz Republic, Nepal, Pakistan, Sri Lanka, Taiwan, Thailand |
| Australian | 2 | Australia (2) |
| Europe | 3 | Poland, all EU (2) |
| North America | 1 | USA |
| South America | 1 | Argentina, Bolivia, Brazil, Chile, Ecuador, French Guyana, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela |
| South Pacific Region | 1 | New Zealand |

Numbers in parentheses indicate how many times the country appeared in publications; names without numbers in parentheses mean the country was studied in only one publication.

The distribution of soil loss estimate values does not follow a normal distribution, but is right-skewed, with the highest density of values concentrated near zero rather than around the central or maximum values (Figure 3). This pattern is evidenced by the discrepant results for mean and median, which had values of 19.61 and 6.5 Mg $ha^{-1}$ $yr^{-1}$, respectively. The lowest value was observed in Australia, with an average of 0.17 Mg $ha^{-1}$ $yr^{-1}$, and the highest value occurred in Taiwan, with 204.05 Mg $ha^{-1}$ $yr^{-1}$.

**Figure 3 – Distribution of soil loss estimates by continent or World region.**




There is a high range of mean soil loss estimates across the countries by continent. In Asia, the values range from 0.40 (China) to 204.05 Mg $ha^{-1}$ $yr^{-1}$ (Taiwan) (Table 3). A similar pattern is found in Africa, where the lowest value is from South Sudan and the highest was found in Uganda. By the other hand, the variability was much lower in Australia (always very low soil loss estimates) and Europe. It is noteworthy that the studies on Europe were conducted for the European Union as a whole, not considering the distinction between the 27 member states of the community.

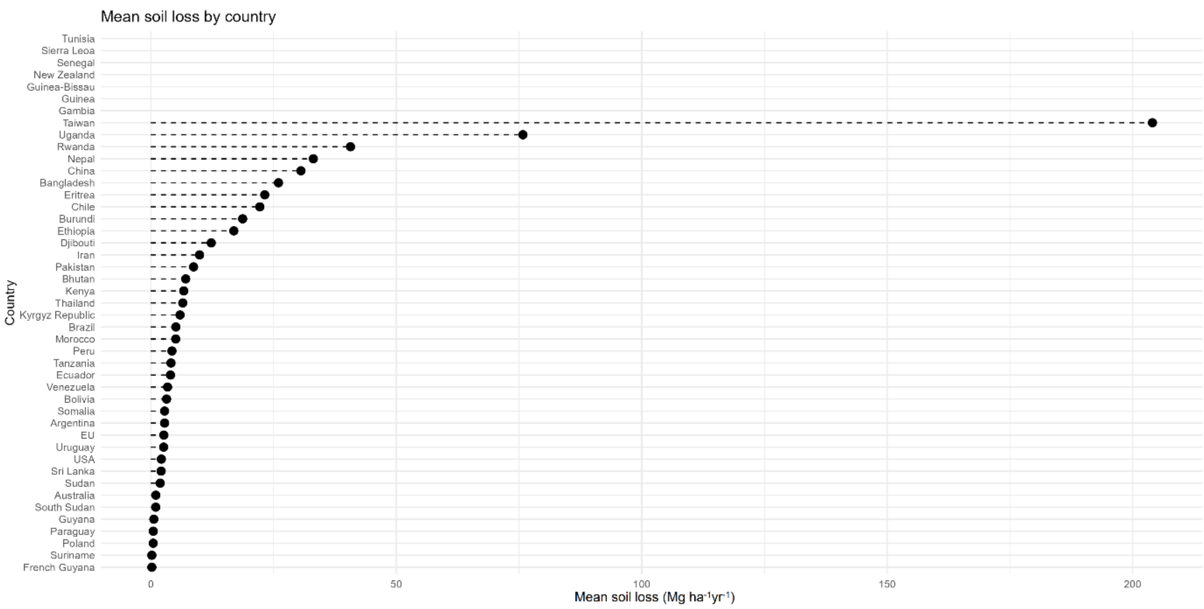
**Table 3 – Descriptive statistics of soil loss estimates (Mg ha$^{-1}$ yr$^{-1}$) at national and supranational scales**

| | N | Mean | Median | Sd. | Min. | Max. | Coef. Var. |
|---|---|---|---|---|---|---|---|
| General | 64 | 19.61 | 6.5 | 35.77 | 0.17 (Australia) | 204.05 (Taiwan) | 1.82 |
| Africa | 21 | 24.41 | 12.3 | 36.27 | 1.00 (South Sudan) | 144.30 (Uganda) | 1.48 |
| Asia | 23 | 32.06 | 26.00 | 46.77 | 0.40 (China) | 204.05 (Taiwan) | 1.46 |
| Australian | 2 | 1.01 | 1.01 | 1.19 | 0.17 (Australia) | 1.86 (Australia) | 1.77 |
| Europe | 3 | 1.92 | 2.22 | 1.32 | 0.48 (Poland) | 3.07 (EU) | 0.69 |
| N. America | 1 | 2.14 | 2.14 | -- | 2.14 (USA) | 2.14 (USA) | -- |
| S. America | 13 | 4.17 | 2.80 | 5.83 | 0.20 (Suriname) | 22.20 (Chile) | 1.40 |

N: number of observations (some countries appear in more than one research); Sd.: standard deviation; Coef. Var: coefficient of variation.

Regarding the mean values of soil loss by country, the higher value was found in Taiwan (only one observation), followed by Uganda, both above 50 Mg ha$^{-1}$ yr$^{-1}$. Countries such as Bangladesh, Burundi, China, Chile, Ethiopia and Nepal have intermediate values. Most countries have low soil loss estimates, under 10 Mg ha$^{-1}$ yr$^{-1}$. Examples are Argentina, Bolivia, Brazil, Ecuador, Paraguay, Poland and USA (Figure 4).

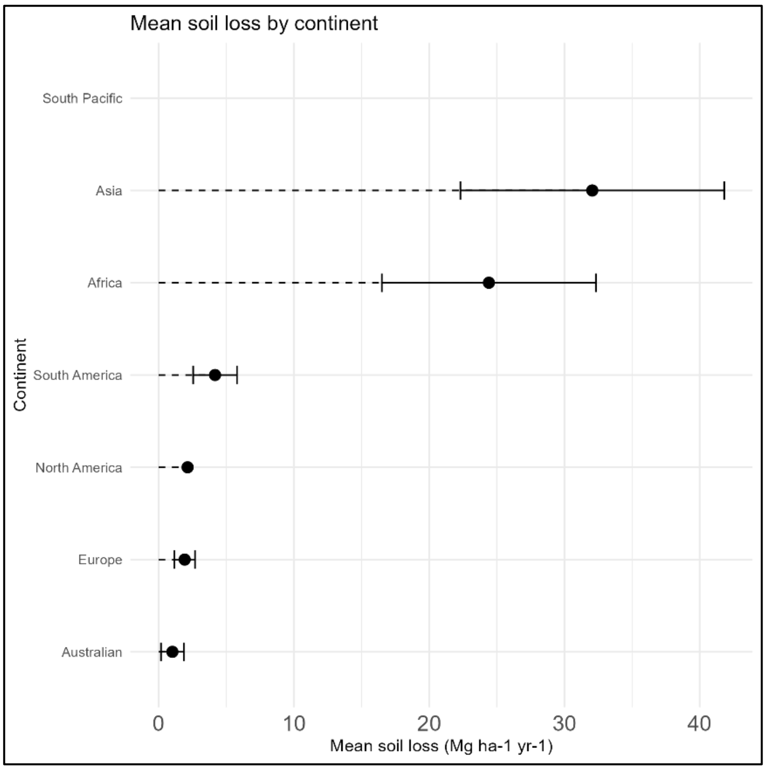
**Figure 4 – Average soil loss estimate by country.**




It was not possible to extract soil loss data for Gambia, Guinea, Guinea-Bissau, New Zealand, Senegal, Sierra Leoa and Tunisia.

When grouping the data by continent, Africa and Asia have the highest averages for water erosion of the soil, while the lowest averages were found in the remaining regions of the World (Figure 5).

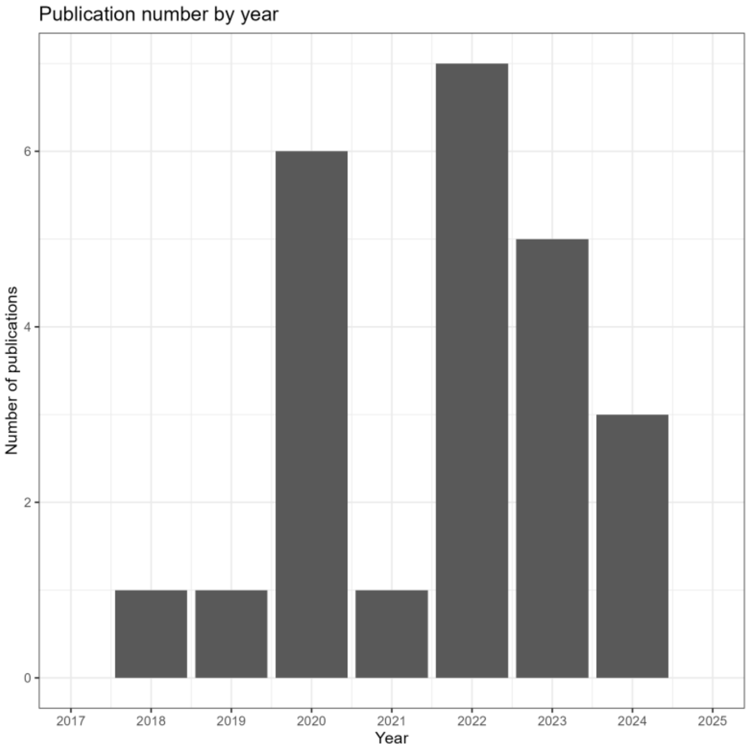
**Figure 5 – Mean of soil loss estimates by continent or World region.**




*2.3.2 Soil Loss Estimates at subnational scales*

Regarding studies that applied RUSLE at subnational scales, such as provinces and states, most were published after 2020, with the highest number of publications in 2022 (Figure 6). The lowest number of studies were found in the years 2018, 2019 and 2021.

**Figure 6 – Number of publications by year for studies at subnational scale (2015-2025).**




Similar to the national-scale RUSLE studies, most publications applying the model on a subnational scale are from Asia, applied in 13 provinces or states of countries such as China, India, Iran, Turkey, and Cambodia (Figure 7, Table 4). The second continent with the most publications in this category is Africa, with research conducted in 5 provinces of Algeria and Nigeria. The European continent has four studies conducted in provinces of Greece, France, and Italy, as well as throughout European Russia. The South American continent has only two studies, one in the state of Espírito Santo, Brazil, and another in the province of Imbabura, Ecuador. There are also two studies conducted in the state of New South Wales, Australia, and on the North and South Islands of New Zealand (*Te Ika-a-Maui* and *Te Waipounamu*, respectively).

Regarding the areas of subnational entities, the largest spatial extent corresponds to European Russia, which represent an aggregated subnational region comprising multiple administrative units and covering more than 3.9 million km². In contrast, New South Wales (Australia) represents the largest single administrative subnational unit included in the analysis, with an area of 801,150 km². The smallest subnational units analyzed was Jijel Province (Algeria, North Africa), covering 2,577 km².

**Figure 7 – Treemap of number of publications that applied RUSLE at subnational scale by continent or World region.**

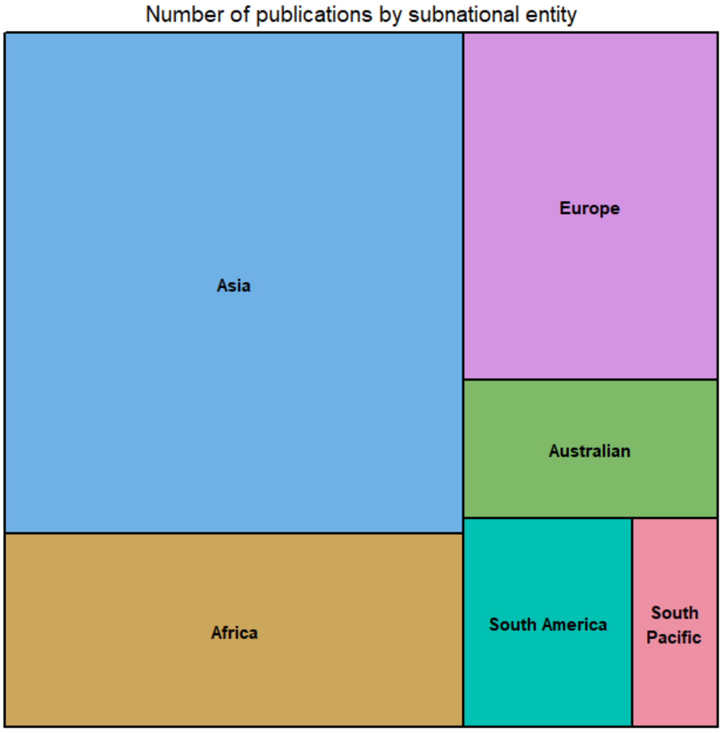



**Table 4 – Distribution of researches that applied RUSLE at subnational scale by continent and nation.**

| Continent | Country | No. | Subnational entity |
|---|---|---|---|
| Africa (5) | Algeria | 2 | Jijel, Tebessa |
| | Nigeria | 3 | Abia, Anambra, Ekiti |
| Asia (13) | Cambodia | 1 | Battambang |
| | China | 7 | Guizhou, Ningxia, Northeast China (Heilongjiang, Jilin, Liaoning and part of Inner Mongolia Autonomous Region), Tibet |
| | India | 3 | Bundelkhand, Goa, Uttakhand |
| | Iran | 1 | Golestan |
| | Turkey | 1 | Ordu |
| Australian continent (2) | Australia | 2 | New South Wales (2) |
| Europe (4) | Greece | 1 | Crete Island |
| | France | 1 | Nor-Pas-de-Calais |
| | Italia | 1 | Basilicata |
| | Russia | 1 | European Russia Macroregion |
| South America (2) | Brazil | 1 | Espírito Santo |
| | Ecuador | 1 | Imbabura |
| South Pacific (2) | New Zealand | 2 | North Island, South Island |

Although the dataset is smaller, the distribution of estimated soil loss values at the subnational scale also does not follow a normal pattern, and is right-skewed, just like the national and supranational datasets (Figure 8). The median is lower than the mean, although the discrepancy is much less pronounced than in the national and supranational data. The mean is 10.99 Mg $ha^{-1}$ $yr^{-1}$, while the median is 6.89 Mg $ha^{-1}$ $yr^{-1}$ (Table 5).

**Figure 8 – Distribution of soil loss estimates by continent, for the studies applying RUSLE at subnational scales.**

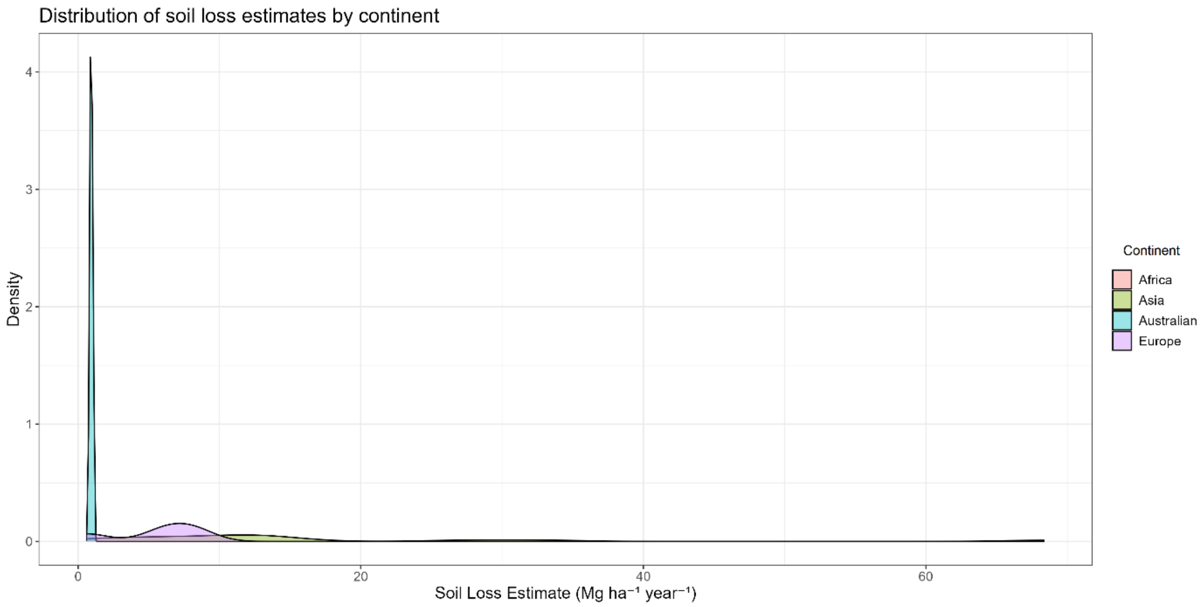



**Table 5 – Descriptive statistics of soil loss estimates at subnational scales**

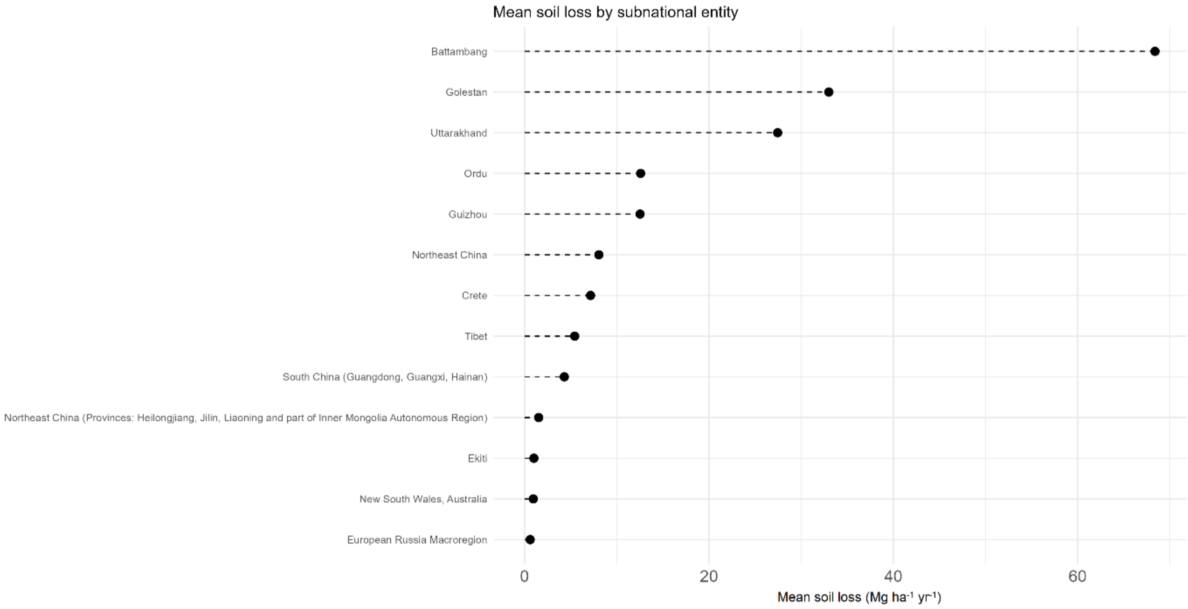
| | N | Mean | Median | Sd. | Min. | Max. | Coef. Var. |
|---|---|---|---|---|---|---|---|
| General | 39 | 10.99 | 6.89 | 15.36 | 0.60 (European Russia) | 68.39 (Battambang, Cambodia) | 1.40 |
| Africa | 5 | 1.00 | 1.00 | -- | 1.00 (Ekiti, Nigeria) | 1.00 (Ekiti, Nigeria) | -- |
| Asia | 17 | 16.55 | 12.43 | 18.01 | 1.52 (Northeast China) | 68.39 (Battambang, Cambodia) | 1.46 |
| Australian | 5 | 0.93 | 0.92 | 0.08 | 0.85 (NSW, Australia) | 1.05 (NSW, Australia) | 0.09 |
| Europe | 8 | 5.51 | 6.49 | 3.45 | 0.60 (European Russia) | 8.45 (Crete, Grecia) | 0.62 |

Soil loss estimates data was not found in the papers of the Americas or South Pacific region.

There is a wide range in soil loss values, varying from less than one to more than 65 Mg of soil eroded annually. The lowest values of soil loss estimates were found in the European Russia, followed by New South Wales, Australia, with a maximum value of 1.05 Mg $ha^{-1}$ $yr^{-1}$.

After calculating the mean soil loss by subnational entity, the highest values are in Battambang (Cambodia), Golestan (Iran), and Uttarakhand (India), which are higher than 20 Mg $ha^{-1}$ $yr^{-1}$ (Figure 9). By the other hand, the lowest means were found in South China (provinces of Guangdong, Guangxi and Hainan), Northeast China (provinces of Heilongjiang, Jilin, Liaoning and part of Inner Mongolia Autonomous Region), Ekiti (Nigeria), New South Wales (Australia) and the European Russia, all with soil loss rates under 5 Mg $ha^{-1}$ $yr^{-1}$.

**Figure 9 – Mean soil loss estimates by subnational entities.**




Due to data unavailability in the reviewed articles, it was not possible to extract mean soil loss values from studies applying RUSLE for the following subnational entities: Abia and Anambra (Nigeria); Basilicata (Italy); Bundelkhand and Goa (India); Ningxia and Central and Western China (China); Espírito Santo (Brazil); Imbabura (Ecuador); Jijel and Tebessa (Algeria); New South Wales (Australia); Nord-Pas-de-Calais (France); and the North Island and South Island of New Zealand.

## 2.4 Discussion

A large variability was observed in the sizes of the study areas evaluated, given that both national and subnational scales were considered. Excluding studies covering the World or entire continents, the largest area studied was China (9.5 million $km^2$), where more than one study applied the RUSLE model (Zhuang et al. 2021; Xiong et al. 2024). On the other hand, the smallest area studied was Jijel (Nehaï & Guettouche, 2020), a province of Algeria, North Africa (2,577 $km^2$). Naturally, this great variability in the area of the territories evaluated by the studies influences the interpretation of the soil erosion values obtained by each study, both at national and supranational scales, as well as at the subnational scale. Emblematic examples include small countries characterized by steep terrain, such as Taiwan, which exhibited the highest soil erosion rates in the dataset: despite its area being smaller than 40,000 $km^2$, soil loss estimates exceed 200 Mg $ha^{-1}$ $yr^{-1}$ (Chen et al., 2023). Conversely, Australia, with a land surface of continental dimensions, presents very low erosion rates, largely due to its drier climate and the predominance of flat relief across much of its territory (Teng et al., 2016; Zhang et al., 2022).

It was possible to observe that soil water erosion varies considerably across the globe, with estimates ranging from 0.17 to 204.0 Mg $ha^{-1}$ $yr^{-1}$, resulting in an overall average of 19.61 Mg $ha^{-1}$ $yr^{-1}$ at national and supranational scales. The same occurs with estimates for subnational entities, but at a lower variability due the smaller dataset. The wide variability in soil loss estimates is primarily due to the equally heterogeneous climatic and geomorphological conditions across the countries, states, provinces and other regions where RUSLE was applied in these studies. Indeed, the R and LS factors, which reflect rainfall and terrain morphology, respectively, were identified as the most prominent in the final model computation results by most studies. The highest soil loss estimate (204 Mg $ha^{-1}$ $yr^{-1}$) was observed in Taiwan (Chen et al. 2023), whose very rugged topography, combined with intense rainfall, results in high potential soil loss. Conversely, the lowest estimate (0.17 Mg $ha^{-1}$ $yr^{-1}$) occurred in Australia (Zhang et al. 2022), where the less humid climate, with the presence of arid deserts and relatively homogeneous relief, resulted in very low soil loss.

Due to the diverse objectives and methodological approaches of the studies in the final dataset, it was not possible to obtain average values for soil erosion estimated by RUSLE for all of these studies. In several cases, RUSLE was applied as a complementary tool alongside other modeling methods to address specific research objectives, such as estimating economic losses from soil erosion and/or assessing water contamination risks, for example. Nevertheless, most publications still reported relevant soil loss information. For example, Wang et al. (2021) observed that soil erosion in China was lower in 2018 than in 1999, a result that aligns with findings from other studies in the region.

Information on the methodologies used to obtain and compute the factors was also taken into account. Because equations and models proposed by various scientists over the past few decades are widely available, various studies have used a wide range of methods to estimate these factors, considering the availability of data and the suitability of the method for the study region. Therefore, some of the variability in soil loss results can be attributed to the methods employed by each study.

To obtain the R-factor, some studies use the formulas proposed by publications related to the original USLE and RUSLE publications (Wischmeier & Smith, 1958; Renard & Freimund, 1994), with adaptations for obtaining data from remote sensing and geospatial processing to apply the equation at the desired scale. Most part of the papers, however, have adopted other methodologies for determine the rainfall erosivity, most of them start with meteorological precipitation data to develop specific equations and models (Yu et al., 1996; Aiello et al., 2015; Klik et al., 2015; Xie et al., 2016).

The same occurs with the K factor (soil erodibility). Classical authors established relationships and formulas between the physical attributes of the soil, such as clay, sand, and silt content to determine its intrinsic erodibility in response to the impact of raindrops (Wischmeier et al., 1971). Although some authors have carried out quite complete and systematic soil sampling of extensive regions, most studies have obtained data already made available by programs of official state agencies (Panagos et al., 2014), either already calculated for the K factor or processed with methodologies proposed by more recent research (Williams et al., 1996; Newsome et al., 2018; Williams, 1995).

The LS factor, related to terrain topography (Wischmeier, 1978), appears to be the most homogeneous in terms of its method of acquisition in the analyzed studies. After the advent of satellites, the Earth's surface was mapped, and the production of digital elevation models (DEM) became increasingly common and available for a wide variety of applications (Guth et al., 2021; Ricker, 2025). These digital models are the basis for virtually all length-slope (LS) factor calculations. However, there are variations in the methodologies by which these DTMs are processed to obtain the LS factor, with adaptations for specific regions being common (Boufala et al., 2020).

The C factor is perhaps the one that allows for the greatest flexibility and variability in its calculation for application in large-scale studies. Several methodologies are available for its estimation, with NDVI (Normalized Difference Vegetation Index) and SAVI (Soil Adjusted Vegetation Index) being very common (Huete et al., 1988). Collections of satellite images from different periods are commonly used to develop average values for obtaining the C factor.

The P factor, that is, the one related to soil conservation practices, was originally conceived to consider the effect of specific practices in mitigating and reducing sheet erosion. Among these practices is the construction of contour terraces. At the local, landscape level, it is possible to determine this factor using tables already calculated in the literature. However, determining the P factor for larger scales, even at the watershed level, is challenging. One strategy is to set its value to 1, that is, to disregard it from the equation (Gourfi et al., 2018). However, another way to take it into account is to assign it to a land use cover category, with data available in GIS products (Lufafa et al., 2003; Wang et al., 2021).

The R and LS factors were highlighted as the most influential in the soil loss estimation results by a large part of the studies. In fact, the rugged topography, associated with high erosivity of precipitation events, has the potential to significantly increase soil disaggregation and surface loading. This is the case in Taiwan, the country that obtained the highest estimate of soil loss (Chen et al., 2023). The island is composed of mountain ranges, located on geological faults under the Western Pacific Ocean (Williams & David, 2008), under a tropical climate, with monsoons and typhoons throughout the year.

Land cover also emerges as a key factor influencing soil erosion, as highlighted by several studies. In general, anthropized soils (that is, soils in which natural vegetation has been modified or removed) exhibit greater susceptibility to erosion. In Europe, arable lands characterized by low plant biomass have been identified as particularly prone to soil erosion (Panagos et al., 2015). Conversely, increased vegetation cover is consistently associated with lower estimated soil loss rates, especially in studies based on temporal analyses (Yao et al., 2024). This relationship is well established in investigations conducted at smaller spatial scales, such as river basins, watersheds, and protected or conservation areas. In tropical regions, where rainfall intensity and erosivity are typically high, vegetation plays a particularly critical role in mitigating soil loss (Smail et al., 2025).

Many papers have studied potential soil erosion over time, sometimes applying trend analysis, such as the Mann-Kendall test (Mann, 1945; Kendall and Stuart, 1976). Most studies examine a time series from the 1990s to the time each article was researched. Soil erosion estimates show highly variable trends, increasing in some regions and decreasing in others. In regions where estimated soil loss has increased, climate change (including increased rainfall and its intensity), along with the suppression of native ecosystems and inappropriate agricultural practices, are associated with the increasing trend in soil loss rates (Wu et al. 2024). On the other hand, in China, several studies indicate a significant reduction in soil loss due to water erosion in recent decades (Zhuang et al. 2021). According to the studies, the C factor of the RUSLE model was a major factor in this reduction, mainly due to the large-scale reforestation programs implemented in several regions of that country since the late 20$^{th}$ century (such as the Great Green Wall Project). In this case, the R factor had a variable influence, with an increasing trend in some regions and a decreasing trend in others (Wang et al. 2021).

Certainly, the varying levels of soil loss across countries alter how nations are also affected environmentally, economically, and socially. From this perspective, applying RUSLE at national and subnational scales is an important tool for applying the model.

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# APPENDIX 1

# FINAL COLLECTION OF PUBLICATIONS

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# SECOND CHAPTER

## Soil loss estimates and analysis of spatial patterns in the Brazilian northeast and southeast: Application of the RUSLE model.

**Abstract**: Water erosion is a major threat to soil conservation, since it is a non-renewable resource fundamental to food security and ecosystems functioning. Estimating soil loss by erosion is important for actions aiming to prevent this process. The Revised Universal Soil Loss Equation (RUSLE) is an empirical model used for this purpose. The remote sensing and Geographic Information Systems (GIS) allow its application at large scale areas. The objective of this work was to produce soil loss estimates by RUSLE model for the Northeast and Southeast macro regions of Brazil, as well to apply a spatial analysis in the data. The five factors of the RUSLE were obtained or estimated using open-source data from satellite imagery, meteorological stations and other Brazilian institutional publications. Spatial analysis was applied to interpreting the results, at states and municipality levels. The final calculation revealed that the major proportion of the area falls into the lower erosion classes, although the southeast has more relative area within high classes of soil loss. Spatial analysis revealed clusters of high erosion rates, which are mainly coincident to hilly, steeper mountain ranges, some of them related to densely industrial, urbanized zones, all in the Southeast region. Low erosion clusters are mainly located in the Northeast region, associated with plain, more forested areas or low rainfall shrubland zones.

**Abstract**: L'erosione idrica rappresenta una delle principali minacce alla conservazione del suolo. Il suolo è una risorsa non rinnovabile fondamentale per la sicurezza alimentare e il funzionamento degli ecosistemi terrestri. Stimare la perdita di suolo dovuta all'erosione è essenziale per pianificare azioni di prevenzione di questo processo. La *Revised Universal Soil Loss Equation* (RUSLE) è un modello empirico ampiamente utilizzato a tale scopo. Il *Remote Sensing* e i *Geographic Information Systems* (GIS) ne consentono l'applicazione su vaste aree. L'obiettivo di questo lavoro è stato quello di produrre stime di perdita di suolo attraverso il modello RUSLE per le macroregioni Nordest e Sudest del Brasile, nonché applicare un'analisi spaziale ai dati. I cinque fattori della RUSLE sono stati ottenuti o stimati utilizzando dati open source provenienti da immagini satellitari, stazioni meteorologiche e altre pubblicazioni istituzionali brasiliane. L'analisi spaziale è stata applicata all'interpretazione dei risultati, a livello statale e municipale. Il calcolo finale ha rivelato che la maggior parte dell'area ricade nelle classi di erosione più basse, sebbene il Sudest presenti una proporzione relativamente maggiore di aree nelle classi di perdita di suolo più elevate. L'analisi spaziale ha evidenziato cluster con alti tassi di erosione, principalmente coincidenti con aree collinari e catene montuose più ripide, alcune delle quali associate a zone densamente industrializzate e urbanizzate, tutte localizzate nella regione Sudest. I cluster a bassa erosione si trovano prevalentemente nella regione Nordest, associati ad aree pianeggianti, più boscose o a zone di arbusteti con basse precipitazioni.

**Resumo**: A erosão hídrica é uma das principais ameaças à conservação do solo, pois trata-se de um recurso não renovável fundamental para a segurança alimentar e o funcionamento dos ecossistemas. Estimar a perda de solo causada pela erosão é essencial para orientar ações de

prevenção desse processo. A Revised Universal Soil Loss Equation (RUSLE) é um modelo empírico amplamente utilizado para esse fim. O sensoriamento remoto e os Sistemas de Informação Geográfica (SIG) permitem sua aplicação em grandes áreas. O objetivo deste trabalho foi produzir estimativas de perda de solo pelo modelo RUSLE para as macro-regiões Nordeste e Sudeste do Brasil, bem como aplicar uma análise espacial aos dados. Os cinco fatores da RUSLE foram obtidos ou estimados a partir de dados de acesso aberto, provenientes de imagens de satélite, estações meteorológicas e outras publicações institucionais brasileiras. A análise espacial foi aplicada na interpretação dos resultados, em níveis estadual e municipal. O cálculo final revelou que a maior parte da área se enquadra nas classes de erosão mais baixas, embora o Sudeste apresente proporção relativamente maior de áreas nas classes de maior perda de solo. A análise espacial identificou agrupamentos de altas taxas de erosão, principalmente coincidentes com áreas colinosas e cadeias montanhosas mais íngremes, algumas associadas a zonas densamente industrializadas e urbanizadas, todas na região Sudeste. Já os agrupamentos de baixa erosão localizam-se predominantemente na região Nordeste, associados a áreas planas, mais florestadas ou a zonas de arbustais de baixa pluviosidade.

### 3.1 Introduction

Soils developed from multiple, combined processes at a very low rate, spanning till to thousands of years (Lima et al. 2022), being thus considered a non-renewable resource (Clunes et al. 2022). It plays pivotal functions, such as organic carbon stock, storing large amounts of water, etc.; overall, the soil is essential for the human livelihood on Earth (Feng et al. 2024). For these reasons, soil conservation is always a relevant concern to maintain its ecosystem and human services as long as possible.

Natural soil erosion is a pivotal process responsible for landscape formation and development. It is a very slow process, usually implying a loss of less than 2 Mg $ha^{-1}$ $yr^{-1}$ in different ecosystems (Nearing et al. 2017). However, human activities such as the monoculture practice, the landscape fragmentation due to urban processes, etc., accelerate soil erosion processes making the soil much more fragile, thus dramatically increasing soil loss rates (Zhao et al. 2019).

The accelerated soil erosion (as an anthropogenic process) leads to considerable types of problems. The loss of the upper soil horizons (organic (O) and organo-mineral (A)) removes the most fertile portion of the pedosystem, consequently decreasing soil fertility in both natural as well as agricultural areas. In natural areas, this can bring, in most dramatic cases, to desertification processes. In agricultural one, this means a dramatic decrease in terms of productivity, thus bringing to an increase in the use of huge amounts of chemical fertilizers, with related issues in terms of (Liu et al. 2021): i) increase in socio-economic costs, ii) environmental pollution and related consequences on human health. Furthermore, an increase in soil erosion rates causes higher sedimentation processes in both natural and artificial inland aquatic ecosystems, such as lakes, thus: i) reducing their water storage capacity; ii) increasing eutrophication processes and, consequently, iii) being responsible for huge damages in aquatic life ecosystems and related socio-economic activities for recreative and profitable purposes (Tibby et al. 2023). In a worldwide context, the most severe form of soil water erosion is responsible for a reduction of more than 33 million tonnes/year of food; this is particularly dramatic for countries strictly dependent on agricultural activities for both their internal and worldwide economy (Sartori et al. 2019). From this point of view, a paradigmatic case is represented by Brazil, considered the "breadbasket of the world" thanks to its leadership in the production of several commodities exported worldwide (Nogueira et al. 2018).

The so-called "*Brazilian agrobusiness*" sector is so important in influencing the entire worldwide agro-economy. This is the reason why, the study of Brazilian soils and issues affecting them, is strategic at the global market size. Additionally, soil erosion is a relevant factor leading to carbon loss from the pedosphere, i.e., the first terrestrial ecosystem in terms of stocked carbon (1.32 Gt), showing its great importance in mitigating and influencing climate change processes; Tropical soils, featuring extended areas of Brazil, are, thanks to their peculiar morphological and physical-chemical properties, among the most soil carbon stocks at worldwide level (Müller-Nedebock and Chaplot 2015). Since its colonization by the Portuguese (1500 DC), large areas of these natural biomes were partially or totally destroyed for timber exploitation, agriculture, livestock, urbanization, etc. Despite the benefits and development for the country, these activities led to huge disturbances in the functioning of the natural ecosystems (Schulz et al. 2017; Bonanomi et al. 2019; de Lima et al. 2020). Undoubtedly, these bring to increased rates in soil loss due to water erosion and, consequently, modifying its natural spatial patterns too. This is particularly true for most developed and urbanized areas, where human and commercial activities are strongly impacted into the soil environment.

Today, Brazil is politically divided into five major regions. The northeast and southeast ones cover almost 2.5 million km², holding 140 million people, i.e. the 65% of the whole Brazilian population. They also represent important commercial and industrial hubs of the country, being the main responsible (c.a. 65/70%) for the Brazilian Gross Domestic Product (GDP) (source: https://www.statista.com). As these regions were the first to suffer the colonization process, their natural biomes were severely devastated. The Atlantic Forest biome is the most deforested in the country, with most of its territory occupied by agricultural activities (Vancine et al. 2024). Next comes the Cerrado, which reached 50% of areas designated for this use last year. The Caatinga, a biome exclusive to the Brazilian Northeast, is also under great pressure, threatening the preservation of the biome in the future (da Silva et al. 2018; Teixeira et al. 2021). In these regions, mainly in the Southeast one, there are vast areas strongly subject to soil erosion, e.g. central areas of the Rio de Janeiro State, along with portions of São Paulo and Minas Gerais States, where soil erosion can reach rates above 100 Mg ha$^{-1}$ yr$^{-1}$, often associated to poor agricultural and soil management (Guerra et al. 2014).

Although soil erosion has been an oscillating concern over the centuries, it was from the late 1800s that more empirical, scientific and systematic studies arose aiming at soil conservation purposes (Dotterweich 2013). From the 1930s soil scholars were already developing models regarding soil losses from water erosion (Renard et al. 1997). The universal soil loss equation (USLE) is a mathematical model proposed by Wischmeier and Smith (1978) aiming to obtain soil loss in agricultural areas in the US. After a series of revisions and advances, in the 1990s the Revised Universal Soil Loss Equation (RUSLE, hereafter) was applied by the United States Department of Agriculture (USDA) (Renard et al. 1997). Briefly, the model considers five multiplicative five factors (vide infra), intrinsic to the soil or related to the climate and vegetation cover.

The RUSLE was profusely applied worldwide for estimating soil loss in regional watersheds and croplands scales (van De 2008). From the past few decades, the advancements of Geographic Information Systems (GIS) and Remote Sensing (RS) technologies allow to calculate/estimate the RUSLE factors in major scales and with reduced costs on data acquisition (Prasannakumar et al. 2012; da Cunha et al. 2017; Phinzi and Ngetar 2019; Räsänen et al. 2023). The main drawbacks of this approach are related with the inaccuracy component of the factors obtained through GIS and RS tools, since these factors should be approximated to the original factors acquisition proposed for RUSLE.

Despite these limitations, applying RUSLE based on GIS and RS tools for large-scale scenarios is very useful as it can offer a comprehensible estimate of potential soil loss along a large territory. In Brazil there are several studies on this topic, most of them applied to watershed and agricultural systems (Lense et al 2023; Barbosa et al. 2024; Santana et al. 2024), although there are works covering much larger scales in the territory (Lense et al. 2021). To go further within deep interpretations of soil loss estimations, spatial analysis techniques are very useful, especially for identifying the distribution of spatial patterns featured by quantifiable risk classes throughout the entire studied area.

In this research we aimed to apply the RUSLE model for estimating the soil loss by water erosion in the northeast and southeast regions of Brazil. We chose these areas because they are the most populated in the country and its natural ecosystems have an old history of land use changes. Through spatial analysis, our results will provide an overall understanding on the soil loss spatial patterns in all the investigated biomes, thus providing data for soil conservation and management practices policies.

## 3.2 Methodology

### *3.2.1 Study Area*

Investigated regions are featured by a wide range of latitudes (from 1° to 25° S), geological, and soil features, leading to diverse climates, from dry, semi-arid in the northeast plateau to tropical wet, without dry season in some coastal zone stretches (Alvares et al. 2013). These different environments resulted in several vegetation physiognomies and biomes, which can be grouped within four phytogeographical domains: Atlantic Forest, Cerrado, Caatinga, and Amazon Forest. Fiaschi and Pirani (2009) provide an exhaustive view of these domains.

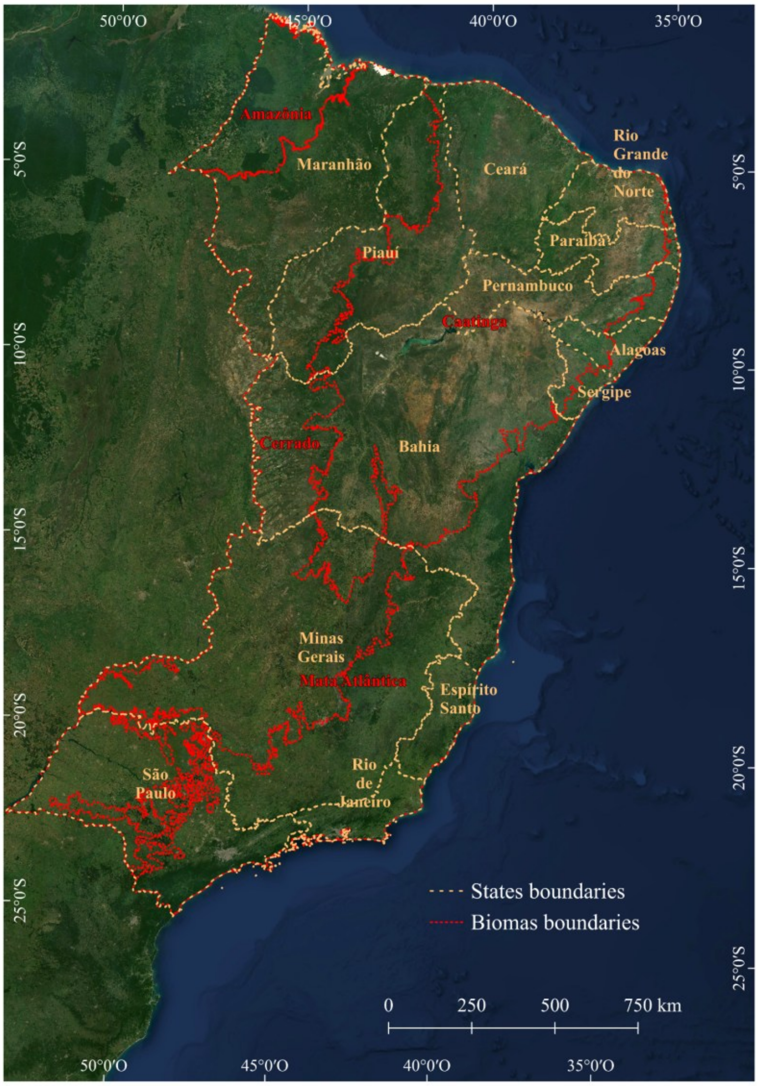
The Atlantic Forests are fragmentally located from the northern coastal zone to the southern regions, which advances inland in the continent. In the coastal zones, the Atlantic Forest comes about evergreen moist tropical forests, while in the inland zones, the drier climate raises seasonal forests, with several deciduous species. The Cerrado is a broad term meaning a wide range of savanna vegetation types placed in the central inland zones, varying from grasslands to sclerophyll open forests (Fiaschi and Pirani 2009). As a phytogeographical domain, the Cerrado holds high diversity of plant habit and species. Caatinga is a dry shrubland to deciduous dry forest covering the inland plateaus of the Northeast Region. Due to the low annual rainfall (< 700 mm) concentrated in a few months, plant species are drought-adapted (sclerophyll, spinescent) (Becerra 2014). Although being a dry environment, Caatinga holds a high species diversity and complex interactions between fauna and flora (Domingos-Melo et al. 2023). The Amazon Domain occurs only in a western section of the Northeast region, in the Maranhão state. The main vegetation type in this area are the "Babaçu" forests, which are evergreen or semi-deciduous forests dominated by *Attalea speciosa* Mart. palm.

The investigated regions cover 2,478,912.4 km², from 1° S to 25° S and from 35° E and 53° E (figure 10). The main geological divisions are basement and sedimentary rocks, along a diverse geological formation, i.e., the São Francisco River Basin, the Parnaíba River Basin and the Paraná

River Basin, together with minor drainage systems in the coastal areas. The main landforms are continental plateaus, with minor areas featured by mountains and coastal plains.

Given the wide scale of the study area, its latitudinal range and topographic features, there is great variation on the climate classification. According to the Köppen climate classification of Brazil (Alvares et al. 2013), the inland northeast macro region has a hot semi-arid climate, surrounded by a tropical savanna climate. The main trait of the semi-arid zone is a low annual rainfall (< 600 mm), with a concentrated distribution of rain in a few months (dos Santos et al. 2024). Along the coastal zone, smaller areas are featured by tropical monsoon and equatorial climates. These wetter climates also appear in the coastal zones of the southeast macro region. which has colder subtropical highlands climates in its inland and by the drier tropical savanna at its western portions (Alvares et al. 2013).

**Figure 10 – Study area. Basemap: The global and cloudless Sentinel-2 map, crafted by EOX, under Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.**




*3.2.2 RUSLE factors*

The RUSLE is a multiplicative model of five variables (Renard et al. 1997):

$$A = R \times K \times LS \times C \times P \quad (1)$$

Where *A* is the estimated annual soil loss (Mg ha$^{-1}$ year$^{-1}$); R is the erosivity power from rainfall (MJmm m$^{-2}$h$^{-1}$); K is the soil intrinsic erodibility factor (Mg ha J$^{-1}$ mm$^{-1}$); LS is the slope length and steepness factor; C is the land cover factor and P is the supporting practices factor. The LS, C, and P factors are dimensionless.

*R factor*

The R-factor describes the rainfall erosivity, in MJmm m$^{-2}$h$^{-1}$. The adopted approach was to estimate the R-factor through the Modified Fournier Index (MFI) calculated from monthly rainfall data. The monthly rainfall data was obtained from Brazil National Institute of Meteorology

(INMET) (https://portal.inmet.gov.br/normais). This database contains the mean monthly rainfall based on the Climatological Normal along 30-years (1981-2010) and coming from 204 meteorological stations distributed within the study area. Then the MFI was calculated according to the equation from Arnoldus (1980):

$$MFI = \frac{\sum_{I=12}^{12} \quad Pi^2}{P} \qquad (2)$$

Where MFI is the Modified Fournier Index; Pi is the mean monthly rainfall (mm); P is the mean annual rainfall (mm).

From the MFI values we calculated the estimated R-factor applying the equation proposed by Arnoldus (1980) for tropical regions:

$$R_e = 1.735 \times 10^{[1.5 \, log \, (MFI) - 0.08188]} \qquad (3)$$

Where $R_e$ is the estimated R-factor and MFI is the calculated Modified Fournier Index.

The estimated R-factor data was georeferenced according to the meteorological stations and then interpolated using regression Kriging using latitude, longitude and altitude as input data (de Mello et al. 2015).

*K factor*

The K factor describes the propensity of soil particles to be disaggregated by the impact energy of raindrops (Renard et al., 1997). We adopted the Soil Erosivity Map to Water Erosion in Brazil (Coelho et al., 2020), which considers intrinsic attributes (organic carbon content, texture, depth, permeability, stoniness and compacted layers). The map comprises five erosivity classes according to the soil units from the Brazilian Soil Classification System (Santos et al., 2018).

*LS factor*

The LS (slope-length and steepness) factor represents the contribution of topography on soil loss estimation, assuming that soil potential erosion is positively related to slope-length (Desmett and Govers 1996). The calculation of the LS-factor was made by using the Digital Elevation Model Global 30 Arc-Second Elevation (GTOPO30) (Earth Resources Observation and Science 2017) as input for SAGA-GIS calculation to the LS-factor based on catchment area derivation (Freeman 1991).

*C factor*

The C-factor is the variable describing the land use cover in the study area. The premise is that different levels of vegetation cover play a range of soil protection against the impacts from rainfall events. Since the northeast and southeast occupy a very large area (on a million square kilometers basis), the chosen approach was to use a Normalized Difference Vegetation Index (NDVI) time series imagery collection to estimate the C-factor (Durigon et al. 2014). Therefore, to obtain an NDVI map of the study area, an average value is calculated using a series (2000-2023) of a MODIS product, more specifically the MODIS Vegetation Indices 16-Day L3 Global 500m, collected as "MODIS Combined 16-Day NDVI" in the Earth Engine data catalog. All operations were performed using Google Earth Engine algorithms. The NDVI is based on red and near infrared spectral regions of reflectance, varying from -1 to 1, where a -1 value implies no dry land surface (like oceans); 0 indicates soil with no green vegetation; and a +1 value would be a dense, full green vegetation (Tucker 1979). There are several equations to convert the ranging -1 to +1 NDVI value into a C-factor value feasible as input for RUSLE. For this study, the equation proposed by Durigon et al. (2014) was used:

$$C_e = \frac{-NDVI + 1}{2} \tag{4}$$

where $C_e$ estimated C-factor and NDVI is the Normalized Difference Vegetation Index.

*P factor*

The Support Practice factor (P) reports the effects of practices that reduce surface runoff, like contouring farming and terracing (Renard et al. 1997). The rationale of the P-factor is the relative decrease in soil erosion after the supportive practices were implemented. Its values range from 0 to 1, where a 0 value means the presence of efficient supportive practices and a 1 value means no implementation or inefficiency of such practices. The approach adopted for the P-factor was to set it as 1 for all the study area (Dapin and Ella 2023), since the huge range of landscapes, land cover, and no possibility of accuracy to determine a value of support practices within the overall study area.

*RUSLE final computation*

All factors were output in a raster format (Geotiff extension) and used in the QGIS raster calculator to produce the final erosion estimation. The latest output is a 500 m resolution raster in a SIRGAS 2000 / Brazil Polyconic reference system (EPSG 5880) (QGIS Development Team 2023).

Given the low accuracy of the results, inevitable at this scale and with the data used, the final values of the estimated soil loss rates were reclassified into the eight classes used by Panagos et al.

(2015) in European soil loss estimates, in Mg $ha^{-1}$: 0-0.5; 0.5-1; 1-2; 2-5; 5-10; 10-20; 20-50 and > 50.

### 3.2.3 Spatial analysis

In order to evaluate the spatial distribution of soil loss rate, a cluster analysis was performed. More specifically, it used a spatial auto-correlation test of local indicators (local indicator of spatial auto-correlation, LISA). The LISA (acronym for Local Indicator of Spatial Autocorrelation) (Anselin 1995) is an index explaining the spatial relationship pattern of a neighborhood parameter (Jesri et al. 2021). This model is currently used in several topics, e.g. health (Parra-Amaya et al. 2016; Huda and Imeo'ah 2023) and economics (Wang et al. 2019). According to Jesri et al. (2021), in order to describe the spatial clustering, a local spatial autocorrelation index is calculated using the following formula:

$$I_i = \frac{X_i - \underline{X}}{S_i^2} \sum_{i=1, j \neq i}^{n} W_{i,j}(X_i - \underline{X}) \qquad (5)$$

Where:

$x_i$ characters of parameter $_i$

$X$ the mean of parameters

$wi$, the matrix of weights that in some cases is equivalent to a binary matrix with ones in position $i,j$

$$S_i^2 = \frac{\sum_{i=1, j \neq i}^{n}}{n-1} \qquad (6)$$

And $n$ the total number of features.

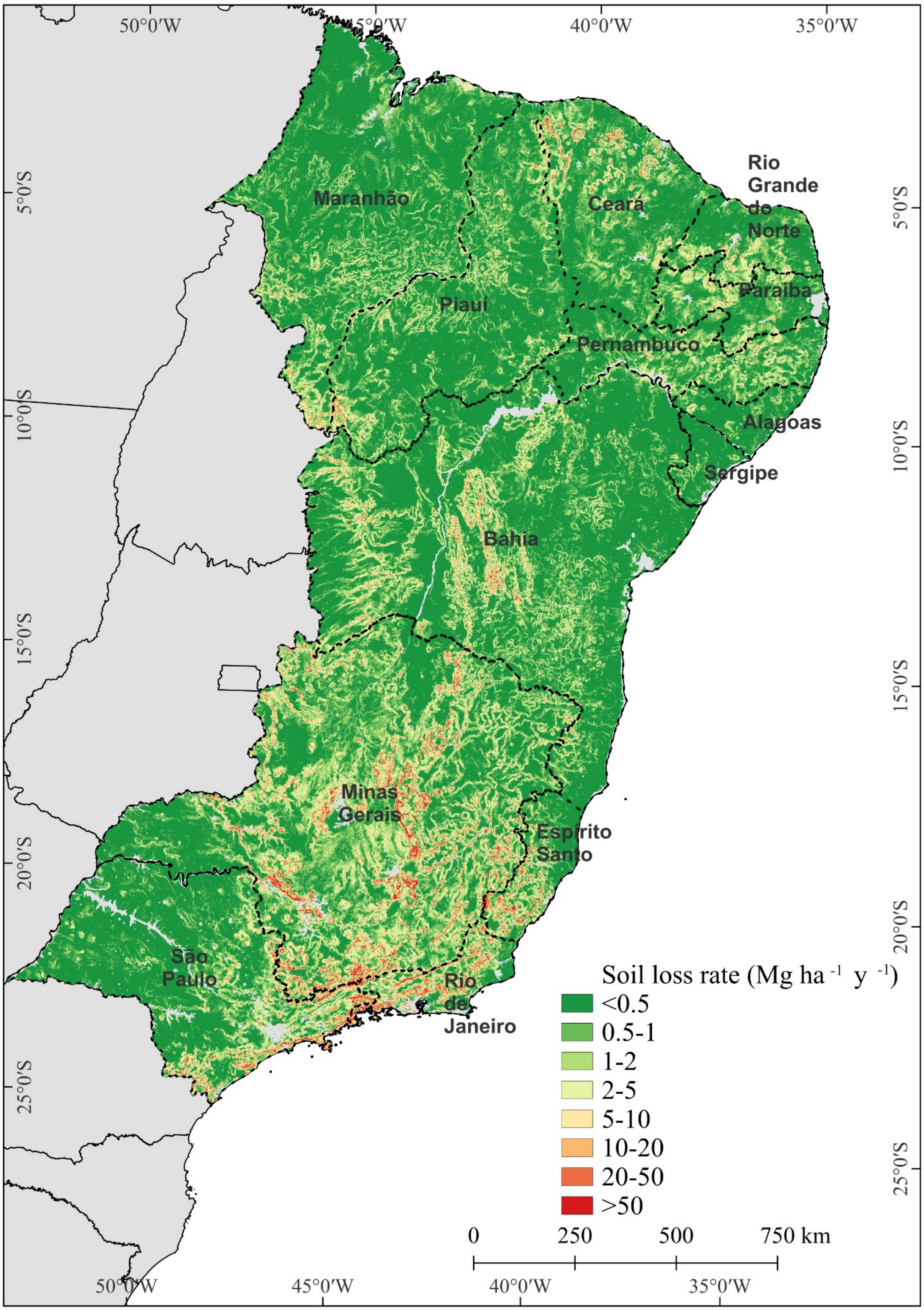
In this work, the model was applied to identify clusterings (hot spots) of states and municipalities with high or low rates of soil loss estimated by the RUSLE procedure. On the basis of Ii, the clusters were classified into four categories: HH (autocorrelation positive, significant, areas of high soil erosion rates with neighbors of high rates, "Hotspot"); HL (autocorrelation negative, significant, areas of high soil erosion rates with neighbors of low rates); LL (autocorrelation positive, significant, areas of low rates with neighbors of low rates, "Coldspot") and LH (autocorrelation negative, significant, areas of low rates with neighbors of high rates). In total, there are 3641 municipalities within the Northeastern and Southeastern macro-regions. A spatial analysis was performed in order to assess patterns of association between the municipalities regarding the soil loss estimates.

## 3.3 Results and discussion

### *3.3.1 Map of soil loss classes*

The map of estimated soil loss by RUSLE for Northeast and Southeast Brazil is shown in Figure 11; its original scale is 1:11000000. A total of 978,296 pixels of 0.5 x 0.5 km were processed and resulted in a total area of 2,445,740.25 km².

**Figure 11 – Map of soil erosion classes in the Northeastern and Southeastern macro regions of Brazil. State boundaries in dashed lines.**

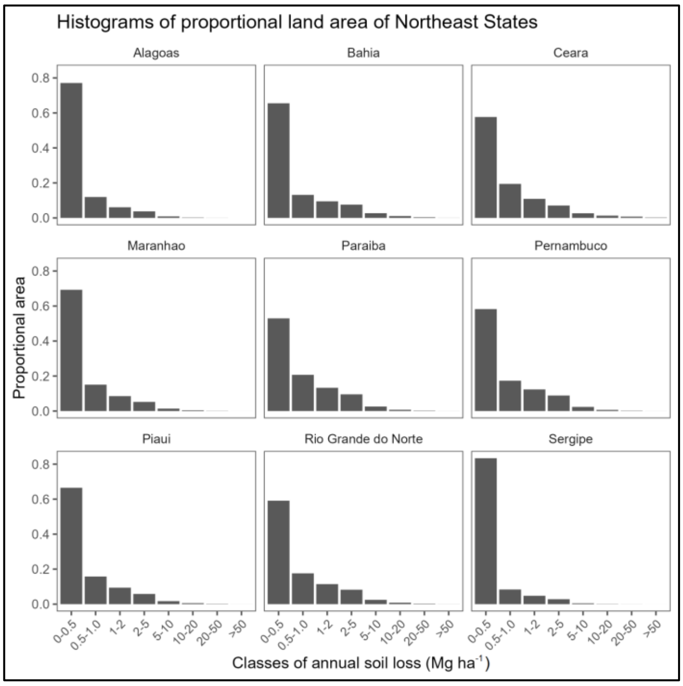



### 3.3.2 Statistics of soil loss rates erosion

#### 3.3.2.1 States

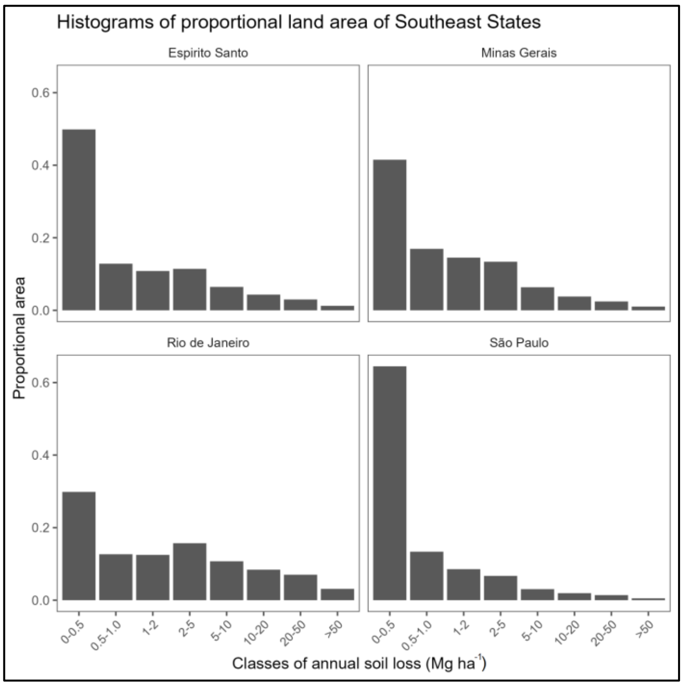
The distribution of soil loss estimates is strongly skewed to the right (Figure 12). This means that most of the recorded values belong to the lower erosion classes. The northeast states have very small area belonging to the higher classes of estimated soil loss, while most of 50% of its territories fall into the lowest erosion estimate (0 - 0.5 Mg $ha^{-1}$ $yr^{-1}$).

**Figure 12 – Histogram of proportional land area distributed in the classes of estimated soil loss rates (Northeast States of Brazil)**




Otherwise, the southeast states have more area distributed in the higher classes of soil erosion (Figure 13). The Rio de Janeiro, Minas Gerais and Espírito Santo States have less than 50% of their land belonging to the 0-0.5 Mg $ha^{-1}$ $yr^{-1}$ class of soil loss. The Rio de Janeiro State has a well-distributed proportion of area across the investigated classes. On the opposite side, the São Paulo State has a higher proportion of land within the first class of soil loss, and a relatively small land area belonging to the higher soil erosion classes.

**Figure 13 – Histogram of proportional land area distributed in the classes of estimated soil loss rates (Southeast States of Brazil).**




Due to the huge observed skewness in the classes of soil loss rates, the median was also calculated in addition to the mean, since it gave far more realistic values for location and data spread (Capra et al. 2014).

Median values show a predominance of low soil losses by water erosion, in all states of the northeast macro region (Table 6). This is due to the fact that the most part of the areas is located within the lowest estimated rate classes. Nevertheless, estimated soil loss values strongly varied along the states: while Alagoas, Paraíba, Pernambuco, Rio Grande do Norte, and Sergipe showed maximum estimated values below 200 Mg ha$^{-1}$ yr$^{-1}$, other states (vide infra) have higher maximum values, like 447 Mg ha$^{-1}$ yr$^{-1}$ in the case of Ceará.

**Table 6 – Descriptive statistics of estimated soil loss rates by the RUSLE model, for the states in the southeast states of Brazil (Mg ha$^{-1}$ yr$^{-1}$).**

| State | Mean (st.dev.) | Variance | Median |
|---|---|---|---|
| Alagoas | 0.52 (1.20) | 1.44 | 0.21 |
| Bahia | 1.05 (3.12) | 9.71 | 0.26 |
| Ceará | 1.41 (5.31) | 28.18 | 0.40 |
| Maranhão | 0.71 (1.72) | 2.98 | 0.27 |
| Paraíba | 1.11 (2.46) | 6.03 | 0.46 |

| | | | |
|---|---|---|---|
| Pernambuco | 1.00 (2.30) | 5.28 | 0.37 |
| Piauí | 0.80 (2.16) | 4.66 | 0.29 |
| Rio Grande do Norte | 1.07 (2.76) | 7.64 | 0.38 |
| Sergipe | 0.40 (1.15) | 1.32 | 0.14 |

On the other hand, the four states of the southeast macro-region reveal very diverse statistics of estimated soil loss (Table 7). These states show strongly higher means and variances of estimated soil erosion.

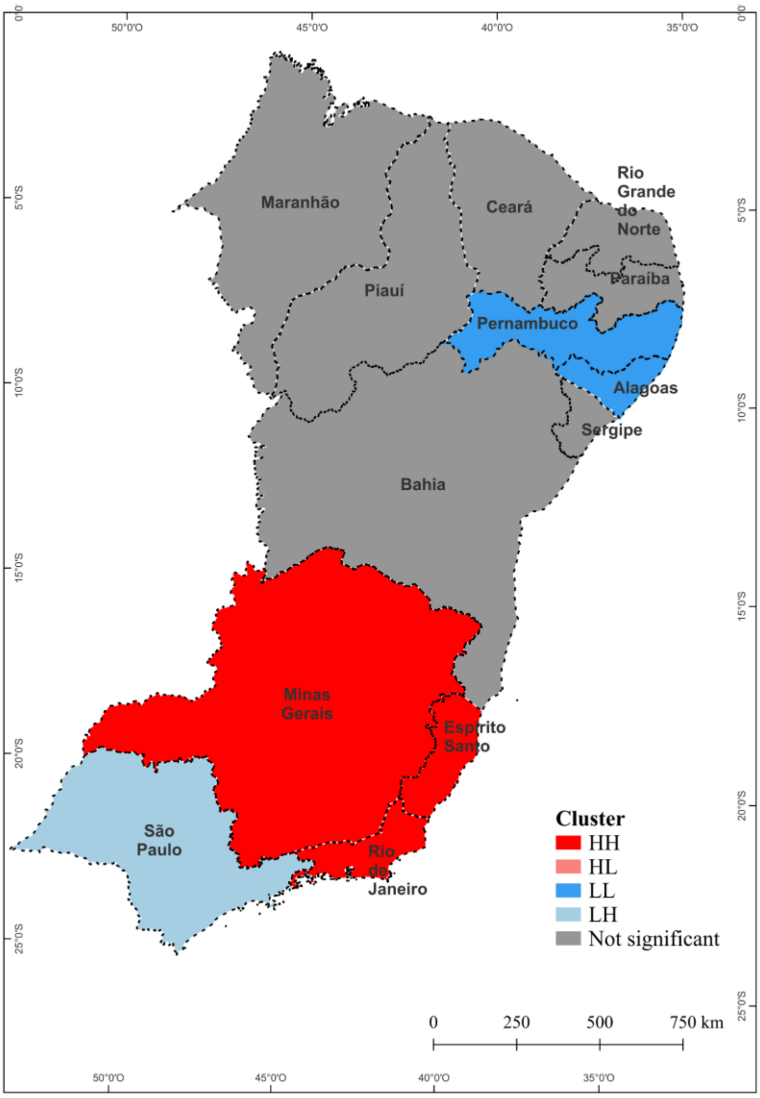
**Table 7 – Descriptive statistics of estimated soil loss rates by the RUSLE model, for the states in the southeast states of Brazil (Mg ha$^{-1}$ yr$^{-1}$).**

| State | Mean (st.dev.) | Variance | Median |
|---|---|---|---|
| Espírito Santo | 3.84 (13.80) | 190.61 | 0.5 |
| Minas Gerais | 3.60 (13.37) | 178.66 | 0.7 |
| Rio de Janeiro | 8.22 (30.83) | 950.38 | 1.5 |
| São Paulo | 1.90 (7.73) | 59.77 | 0.3 |

### *3.3.3 Spatial Analysis*

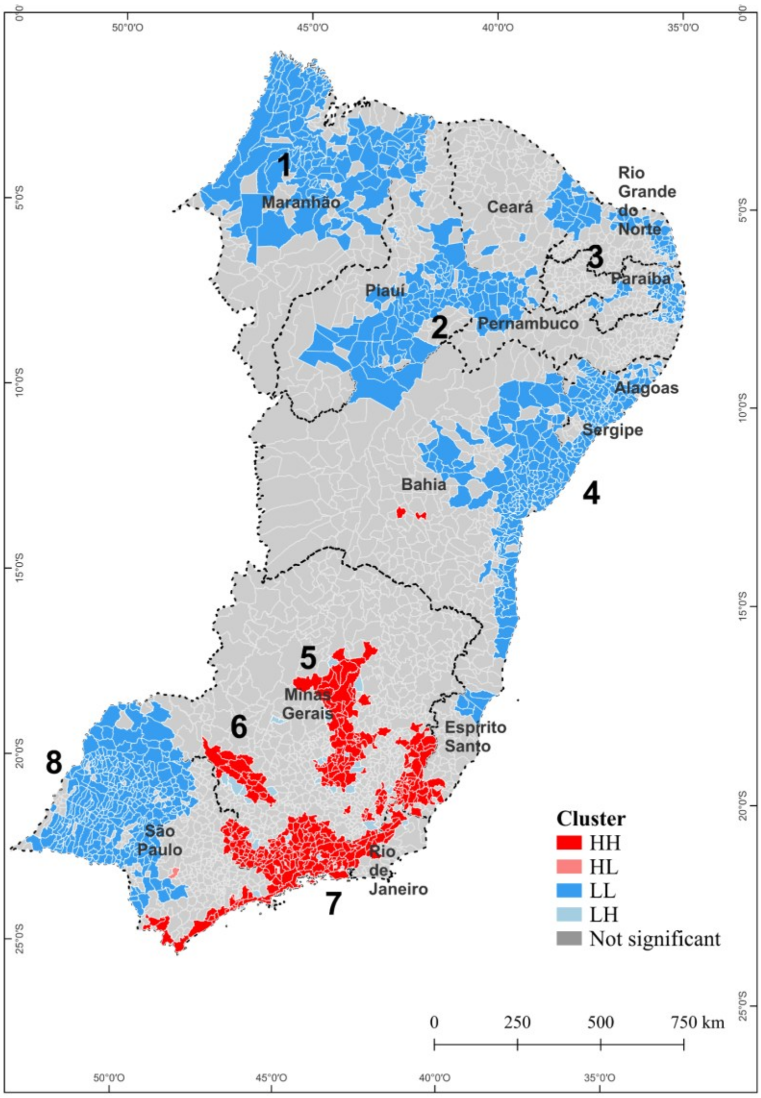
The southeast states of Minas Gerais, Rio de Janeiro and Espírito Santo compose an HH cluster type, *i.e.*, areas of high soil erosion rates with neighbors of high rates too (figure 14). On the opposite side, the São Paulo State is classified as a single LH cluster, being featured by low rates while neighbors are affected by high rates. Only a LL type cluster (low rates and neighbor of low rates) was found, i.e., the States of Pernambuco and Alagoas, in the northeast macro-region.

**Figure 14 – Clusters of the states according to the LISA model. HH: high-high; HL: high-low; LL: low-low; LH: low-high values of autocorrelation and values of estimated soil erosion rates.**




Regarding the municipalities, the LISA model was able to find several large clusters. In total, there are 1645 municipalities with significant values of Local Indicator Spatial Association. It was possible to outline four main clusters of either High-High and Low-Low ranking of spatial association values, for a total amount of 1591 municipalities belonging to the four clusters in each macro-region (Northeast and Southeast) (figure 15, tables 8 and 9).

**Figure 15 – Clusters of the municipalities outlined by the LISA model technique. HH: high-high; HL: high-low; LL: low-low; LH: low-high values of autocorrelation and values of soil erosion rates estimates.**




The Northeast macro-region holds one of the Low-Low municipalities clusters, while High-High clusters are mainly in the southeast macro-region. It is noteworthy to note that three High-High clusters are within Minas Gerais state. Moreover, these clusters are always overlapped within the Atlantic Rainforest and/or Cerrado biomes.

**Table 8 – Descriptive summary of northeast macro-region municipalities clusters obtained by the Local Index of Spatial Autocorrelation (LISA) Model (significant: $p < 0.05$). Total: 783 municipalities in four clusters.**

| Hotspot | Cluster ID | Municipalities | States | Biomes |
|---|---|---|---|---|
| Low-Low | 01 | 167 | Maranhão (148) | Cerrado (86) |
| | | | Piauí (19) | Amazônia (79) |
| | | | | Caatinga (2) |
| Low-Low | 02 | 125 | Piauí (90) | Caatinga (106) |
| | | | Ceará (19) | Cerrado (19) |

| | | | | |
|---|---|---|---|---|
| | | | Pernambuco (10)<br>Bahia (4)<br>Paraíba (2) | |
| Low-Low | 03 | 149 | Paraíba (69)<br>Rio Grande do Norte (46)<br>Pernambuco (23)<br>Ceará (11) | Caatinga (103)<br>Atlantic Rainforest (46) |
| Low-Low | 04 | 342 | Bahia (187)<br>Sergipe (78)<br>Alagoas (77) | Atlantic Rainforest (203)<br>Caatinga (139) |

Within brackets the numbers of municipalities within each State or Biome, for each cluster.

783 municipalities were grouped into four clusters in the Northeastern macro region, all belonging to the Low-Low category (low soil loss estimates and low level of significance). The cluster 01 is mainly in the northern part of the Maranhão State, extending over the Amazon Rainforest and Cerrado biomes, which have no steep areas. The cluster 02 is located in the inland of five states within the Caatinga biome, i.e., marked by low annual precipitation, despite it being featured by different relief units. The coastal areas of the northeast macro-region also hold clusters 03 and 04, which embrace municipalities within the Caatinga and Rainforest biomes, both located on plain, very flat areas.

**Table 9 – Descriptive summary of southeast macro-region municipalities clusters obtained by the Local Index of Spatial Autocorrelation (LISA) Model (significance: p < 0.05). Total: 808 municipalities in four clusters.**

| Hotspot | Cluster ID | Municipalities | States | Biomes |
|---|---|---|---|---|
| High-High | 05 | 91 | Minas Gerais (91) | Atlantic Rainforest (52)<br>Cerrado (39) |
| High-High | 06 | 20 | Minas Gerais (20) | Cerrado (16)<br>Atlantic Rainforest (4) |
| High-High | 07 | 250 | Minas Gerais (121)<br>São Paulo (59)<br>Rio de Janeiro (48)<br>Espírito Santo (22) | Atlantic Rainforest (249)<br>Cerrado (1) |
| Low-Low | 08 | 447 | São Paulo (410)<br>Minas Gerais (37) | Atlantic Rainforest (309)<br>Cerrado (138) |

In brackets the number of municipalities within each State or Biome, for each cluster.

In the Southeast macro region there are 808 municipalities distributed in four clusters (three with High-High values; one with Low-Low). The most frequent biome in these clusters is the Atlantic Rainforest, except for cluster 06, which is into a far inland area where the Cerrado (tropical Brazilian savanna) is the dominant ecosystem. All three clusters of high estimated soil loss overlap mountain ranges. The clusters 05 and 06 are within the Espinhaço and the Canastra Mountain Ranges in the states of Minas Gerais. The cluster 07 is located across the Serra do Mar Mountain Range, from the Southern Espírito Santo State to the Southern São Paulo State, bordering the coastal line of the continent. There are also some scarce LH clusters of a few municipalities around the three HH clusters.

The only Low-Low cluster in the southeast macro-region (cluster 08 in figure 15) is located in the western zone of São Paulo and southwest Minas Gerais States, being preponderantly upon the sedimentary inland plateaus and was originally covered by the Atlantic Rainforest and Cerrado biomes.

### 3.4 Discussion

The obtained final map of estimated soil erosion by RUSLE shows a range similar to those found for the European Union and Australia by Panagos et al. (2015) and Teng et al. (2016). However, in our raw data the overall range includes very high estimated soil losses up to more than 1000 Mg $ha^{-1}$ $yr^{-1}$. The observed differences can greatly depend on the type and source of input data used in the model (Panagos et al., 2015).

In the case of the highest values of soil loss estimation it must be taken into account the expected limitations on the LS and C factors methodologies. In fact, the estimation of the topographic factor (LS) through remote sensing techniques always carries inaccuracy according to the adopted approach (Panagos et al., 2015). The digital elevation model used here has a spatial resolution of 30-arc second (approximately 1 km grid), which can generate inaccuracies in the LS factor calculation. Indeed, the C factor obtained by spectral index imagery can overestimate the final soil loss in steep mountainous areas, such as rock outcrops, i.e., areas without soil and high surface rockiness. A similar overestimation of RUSLE results is known for Australia, due to poor soil cover, which is a natural feature of their ecosystems (Panagos et al., 2015). On the other hand, it was considered useful to use these data in order to optimize the data resampling operations, so as to have the factors with the closest possible cell size. The final soil loss map resolution can therefore be considered a necessary compromise.

The major concentration of land area within higher classes of estimated soil loss is located in the southeast macro-region of Brazil, and is coincident with the great mountain ranges in these areas, notably the Serra da Mantiqueira, Serra da Canastra and Serra do Espinhaço. The general landform of these areas are hills featured by a broad range of steepness, almost entirely converted from its natural biome (mainly Atlantic Forest or Cerrado) to agricultural or livestock lands. However, in the most rugged areas, a cliff and steep topography prevails, often featuring rock outcrops surfaces. In these areas, especially those with shadow soils, there is a very low forest cover, thus hampering soil erosion issues and, consequently, sedimentation processes and deposition in inland waters (Magdalena et al., 2022).

Northeastern macro-regions featured by higher classes of estimated soil loss are mainly limited to those associated with small mountain terrains, such as the Borborema Plateau and the Chapada Diamantina mountain range, both featuring the Caatinga shrublands as the main biome, although in the higher altitude lands are covered by natural herbaceous vegetation (Funch et al., 2007). Nevertheless, most soils of this biogeographical domain have low clay and organic matter contents, mainly due to their natural genesis (Pontes et al., 2022). However, the low annual rainfall and the gentle topography (resulting in low R and LS factors, respectively) bring to low estimated soil erosion values (Bresciani et al., 2023).

Two biomes have the higher influence in the areas featured by the higher classes of estimated soil loss: The Atlantic Forests and the Cerrado. The main natural feature contributing to the incidence of high estimated soil loss is the topographic factor (LS), due to the presence of large mountains and hills, many of them belonging to the Serra do Mar mountain range (Great Escarpment, in a free translation), a series of mountain systems which runs parallel to the Atlantic Ocean from about 13° to 30° S latitude, that split the coastal areas from the inland plateaus of the country (Gomes et al., 2022). Deep slopes, shallow soils and often high-altitude grassland vegetation are associated with strong environmental vulnerability, mainly due to soil degradation by erosion, making these areas of priority in terms of best management and conservation practices (Costa et al., 2020).

Although originally covered by the Atlantic Rainforest together with high-altitude grasslands, many areas along the southeastern mountains were affected by deforestation for the coffee culture purpose (from the 19th century), followed by a conversion to pasture until today (Gomes et al., 2020). Even though the grass cover offers some protection against water erosion, poor pasture management leads to reduction in soil cover, leaving it prone to surface erosion during rainfall events (Renard et al., 1997). In fact, pasture land set in younger soils featuring high slopes is associated with high sediment processes in the inland aquatic ecosystem (Simões et al., 2021). Regarding this type of land use, it was demonstrated that natural forest cover promotes improvements of soil physical features involved in water infiltration, which reduces the potential for surface and deep erosion (Pinto et al., 2018).

The Minas Gerais State holds the main mining industries of the country, concentrating their activities mainly on iron, gold and bauxite reserves (OECD 2022). Mining processes generate several socio-economic and environmental issues. Tailing dams are high-impact dams built to store wet, unstable mining by-products (tailing ore), requiring intensive monitoring and prevention efforts to avoid structural failures causing catastrophic disasters (Belanović Simić et al., 2023; Pereira et al., 2024). In the State, there are at least 390 tailing dams, which risk analysis is supposed to be underestimated (Garcia et al., 2017). In the last decade, indeed, two great disasters took place: The Bento Rodrigues (2015) and Brumadinho (2019) dam disasters, with more than 280 casualties and huge economic losses, besides several environmental impacts downstream the drainage basin, mainly Atlantic Rainforest sensible ecosystems (Garcia et al., 2017; Silva-Rotta et al., 2020). Studies have shown that surface water flowing into the dam's catchment area is a contributing factor to dam instability and potential collapse (Pereira et al., 2024). Thus, the situation is even worse in a scenario of soil erosion, by which soil material comes with the waterflow from surrounding areas and is sedimented on the dam's surface. The great clustering of municipalities with high estimated soil loss rates, combined with the rugged topography, add a risk component with the potential to be more deeply investigated shortly to monitor tailing dams while avoiding following dramatic consequences.

The cluster 07, in the coastal zone of the southeast macro-region, is composed of municipalities belonging to the Serra do Mar mountain range. In particular, in this area are located the two largest Brazilian metropolitan centers (Rio de Janeiro and São Paulo). The fast urban growth brings environmental risks regarding soil conservation. Despite the preservation efforts to maintain the Atlantic Rainforest remnants in these areas, it is expected that all the non-protected areas will be under urbanization processes until 2030 (Daunt et al., 2019). This raises relevant concerns about soil erosion, since unplanned urban expansion is a contributor factor to soil destabilization, due to vegetation clearance, irregular disposal of construction wastes, and poor or wrong management of surface rainwater (Ercoli et al., 2020). In view of this, policies seeking to promote more sustainable urbanization processes (Wang et al., 2018) are strongly recommended for mitigating and preventing soil erosion processes in these densely populated areas in the near future.

In the northeast macro-region, the implementation of good management practices by the small property farmers is pivotal for the preservation of soil from water erosion in soils more susceptible to water erosion (Oliveira et al., 2024). Indeed, cultivated lands are among the most contributing factors leading to higher erosion rates (Barbosa et al., 2024). Although a large portion of this macro region is within the Caatinga biome, with low annual rainfall, higher soil loss from water erosion can occur during concentrated rains in the brief three-month wet season (Becerra, 2014). Despite the low R-factor of this region and overall low estimated soil loss, extreme heavy rainfall events have been occurring more frequently in recent decades (dos Santos et al., 2024). In addition, the urban zones require attention, as they are more susceptible to erosion processes related to urbanization issues (Guerra et al., 2014). Consequently, actions are required in the field of soil erosion control measures, in terms of improving of Land use and urban policy. In fact, one of the main scopes of the presented approach is to emphasize the need to diversify the soil protection action between the States (and also the municipalities); in this way the financial and economic resources can be used more efficiently.

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