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Geospatial Modeling and Mapping of Soil Erosion in India

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Abstract

Soil erosion generally removes the topmost fertile layer of soil, affecting agricultural productivity on a larger scale. As a significant portion of the Indian economy depends on agricultural productivity, granular assessment of the impact of soil erosion becomes critical. However, a national-scale assessment of soil erosion and an impact classification system currently doesn't exist over India. Given the resource-intensive and time-consuming nature of field experiments required for the measurement of soil loss across a vast country, the Revised Universal Soil Loss Equation (RUSLE) was extensively utilized for soil erosion calculations due to its simplicity, streamlined data requirements, and accuracy. This study estimates the yearly potential soil loss throughout India at a spatial resolution of 250 meters and quantifies its variability considering districts, soil texture, soil type, land use and land cover, and basins. The relative importance of individual and combined impact of multiple parameters on quantified soil loss has been assessed using a random forest model. Rainfall erosivity (R-factor) emerges as the most crucial feature in estimating soil erosion in Indian conditions while rainfall intensity, combined with the topographic factor, demonstrated the highest influence on soil erosion in Indian conditions when the combined impact was assessed. Further, we mapped the Sediment Delivery Ratio (SDR) and Specific Sediment Yield (SSY) to assess the actual soil loss reaching downstream of basins across the national boundary. The national mean values for Sediment Delivery Ratio (SDR) and Sediment Yield (SSY) stand at 0.11 and 2.61 tons per hectare per year, respectively. The yearly potential soil loss for India is calculated at 21 tons per hectare per year, and nine out of the twenty districts with the highest susceptibility to soil erosion are in the state of Assam. Finally, a novel impact-based erosion-severity classification system has been introduced which finds that 29.46% of the landmass is prone to minor erosion while 3.17% experiences catastrophic erosion. This is the first comprehensive national-scale assessment of both soil erosion and sediment yield mapping over India, and the consequent classification system will enable the planning and implementation of soil conservation strategies locally as well as nationally.

Keywords: Soil erosion; Sediment Delivery Ratio (SDR); Specific Sediment Yield (SSY); Soil Conservation; India.

1. Introduction

Soil erosion is a global problem, which has led to the destruction of agricultural outcome, fertility of the soil, landslides, and water resources systems (Cunha et al., 2022; Elnashar et al., 2021; Kazamias et al., 2017; Panagos et al., 2019). Recently, there has been a notable increase in the change in land use and land cover (LULC), primarily attributed to deforestation and rigorous farming practices, which has exposed soil surfaces to water erosion (Gomiero, 2016; Milazzo et al., 2022). Moreover, unplanned land use for infrastructural development and the increasing population has reduced forest cover, accelerating soil erosion (Razali et al., 2018). Out of the 1964.4 million hectares (M-ha) of worldwide land degraded by human activities, nearly 1903 M-ha is degraded by water-induced erosion (Bhattacharyya et al., 2015). Erosion is the most dominating erosive agent among all the others (Juez et al., 2018; Sharma et al., 2022). According to the Centre Soil and Water Conservation, Research and Training Institute (CSWCRTI), Dogra, (2011) report, around 68.4% of the total eroded land of India is due to water-induced erosion, with approximately 29% of this eroded soil being transported to sea and permanently lost (Narayana and Babu, 1983). Surface runoff is the most important parameter contributing to soil erosion, according to the data received from the National Bureau of Soil Survey and Land Use Planning (NBBS and LUP). Soil erosion causes the loss of major nutrients (about 74 million tons) from the soil surface each year, resulting in a financial loss of around 68 billion rupees per year in India, considering crop productivity, land-use intensity, and changes in the farming patterns (Bhattacharyya et al., 2015; Lal, 2015). Monitoring and estimating soil erosion on-site is a laborious and expensive process, usually limited to small in-situ experimental setups. To evaluate the scope of erosion triggered by water on a nationwide scale, there is a need for a comprehensive soil erosion model, which is currently unavailable.

A number of physical and empirical models have been formulated to simulate soil erosion. These models incorporate geographic information system (GIS) and remote sensing (RS) technologies at diverse spatiotemporal scales (Kazamias and Sapountzis, 2017; Nekhay et al., 2009; Swarnkar et al., 2018; Wu and Wang, 2007; Zhang et al., 2021). While numerous physical models are available worldwide for assessing soil loss, they differ, particularly in input data and the model application (Asheghi and Hosseini, 2020; Kashiwar et al., 2022; Li et al., 2017; Thomas et al., 2018). Models such as CREAMS (Knisel, 1980), ANSWERS (Beasley et al., 1980), EPIC (Williams, 1990), Guest (Rose, 1999), WEPP (Flanagan and Nearing, 1995), and EUROSEM (Morgan et al., 1998), are available for assessing hydrological and sedimentation phenomena using mathematical equations (Kazamias and Sapountzis, 2017).

However, they may not be suitable for larger nations such as India due to variations in topography and the unavailability of necessary spatiotemporal datasets (Kayet et al., 2018).

On the contrary, the universal soil loss equation (USLE) (Wischmeier and Smith, 1978) and its revised form (RUSLE) (Renard et al., 1991) are empirical models that have been globally employed for the calculation of long-term annual soil erosion over small to medium and large watersheds in India because of low data requirement, robustness, and simplicity (Balasubramani et al., 2015; Shinde et al., 2010). More than 500 studies and investigations have been performed across the globe using the RUSLE method (Borrelli et al., 2021) according to the GASEMT (Global Applications of Soil Erosion Modelling Tracker) database.

Several factors control the sediment yield phenomena in a watershed, such as topography, morphology, lithology, drainage network, LULC type, and climate characteristics (Löbmann et al., 2022; Syvitski and Milliman, 2007; Wang et al., 2021). Many studies have attempted to calculate sediment yield by considering the integrated effect of a watershed's hydroclimatic and morphometric parameters (Rajbanshi and Bhattacharya, 2020; Restrepo et al., 2006). Nevertheless, given the incomplete hydrological coverage of river basins in India, the utilization of geostatistical models becomes indispensable for the robust estimation of soil erosion or the intricate processes of sediment transport and deposition on a considerably large scale. Past studies conducted in India (Jain and Kothyari, 2000; Shinde et al., 2010) were confined to quantifying the Sediment Yield Rate and Specific Sediment Yield, which is inadequate to apply the watershed management strategies at a river-basin scale.

There has been no national-scale assessment of soil erosion across India. While a global study by Panagos et al. (2017) estimated soil loss (t/ha/yr) worldwide, they utilized an average of only seven years of rainfall intensity data for the estimation of rainfall erosivity, a crucial factor in soil loss estimation. However, Vantas et al. (2019) emphasized in their study that a minimum of twenty years of rainfall records is necessary to estimate long-term average rainfall intensity, addressing bias introduced by dry and wet seasons. In our study, we used rainfall erosivity estimations from Raj et al. (2022), who employed forty years of rainfall intensity data to overcome this limitation, enabling a comprehensive and detailed estimation of rainfall erosivity and, ultimately, soil loss (t/ha/yr) in India.

Furthermore, there are no national-scale estimates for other critical aspects of soil erosion modeling in India, such as slope and steepness, cover management, and support practice factors. Soil erosion studies in India have been limited to watershed or sub-watershed scales, as seen in works by Prasannakumar et al. (2012) for the Pamba river basin in Kerala, Dabral et al. (2008) for Papum Pare and Lakhimpur regions of Arunachal Pradesh and Assam, and Biswas and Pani (2015) for the Barakar river basin in the Jharkhand state. The absence of comprehensive and detailed estimates of soil erosion and associated factors, such as slope and steepness, cover management, and support practice factors, prompted us to pursue national-scale estimates of soil erosion across India. In this research, we also examined the importance of contributing factors like rainfall intensity, soil properties, LULC, and agricultural practices on the soil erosion process in Indian condition using the Random Forest algorithm in machine learning. This paper reports the development of a soil erosion model at a national scale, utilizing the f RUSLE empirical model to compute the potential soil erosion (measured in t/ha/yr) at a spatial resolution of 250 meters. A sediment delivery model is then integrated and calibrated with observed sediment load measurements, and sediment delivery ratio (SDR) and sediment yield (SY) were computed for all major river basins. Finally, a new erosion-severity classification system has been implemented to develop a national soil erosion susceptibility map to classify and visualize areas suffering from erosion in India.

2. Materials and methods

2.1 Study area

This research encompasses the geopolitical boundaries of India, comprising twenty-eight states and eight union territories. The nation receives an average of 877.2 millimeters of precipitation (or around 74% of the total annual precipitation of 1182.8 millimeters) in the Monsoon season (Singhvi and Krishnan, 2014). Average rainfall (mm) for the study region is mapped and shown in Figure 1(c) considering IMD (India Meteorological Department) daily rainfall from 1901 to 2016 at 25 km spatial resolution. Higher amount of rainfall could be seen in the northeastern and southern belt of India. Indian climate is primarily influenced by the monsoons. Considering average annual rainfall, Cherrapunji gets highest (11410 mm) and Jaisalmer gets lowest (130 mm) rainfall amount in India (Singhvi, 2014). Agricultural land covers the most prominent land use and land cover area, approximately 60%, while the built-up area covers the least, around less than 1% (Figure 1(a)). The LULC of the study region (India) is dominated by forest land surrounding about 25% of the area, while barren land occupies approximately 14%. Agricultural land use encompasses Kharif crop, Zaid crop, Rabi crop, Double/Triple crop, plantation, shifting cultivation and current fallow LULC classes. Forest class covers littoral swamp, evergreen, deciduous, and degraded type forests. Four soil types, namely Luvisols, Vertisols, Cambisols, and Lithosols, cover about 70% of the country's area, with the remaining 30% covered by the other 14 soil classes (Figure 1(b)). Loamy soil is the most dominant texture class, covering about 46% of the area, while sandy soil covers the least at 16%, as per the texture classes by National Bureau of Soil Survey, Land Use Planning, India. Waterbodies cover around 4.5% of the total area, while mountains and the Rann of Kutch cover about 3.5%. The variations in soil, slope, and LULC classes across India are not uniform, highlighting the need to account for them in a national-scale analysis of soil erosion. The topography map, illustrating elevations across the nation, is presented in Figure 1(d). The extreme northern part of the country, as well as some portions of the northeast, features high-elevation regions, while the lower northern and middle portions exhibit lower elevation ranges, primarily comprising plains. The names of some crucial states, considering this study, have been highlighted in Figure 1(c and d) as follows: Jammu and Kashmir (JK), Himachal Pradesh (HP), Uttarakhand (UK), Uttar Pradesh (UP), Bihar (BH), West Bengal (WB), Assam (AS), Meghalaya (MG), Rajasthan (RJ), Madhya Pradesh (MP), Maharashtra (MH), Gujarat (GJ), Jharkhand (JH), Odisha (OD), Karnataka (KT), and Kerala (KL).

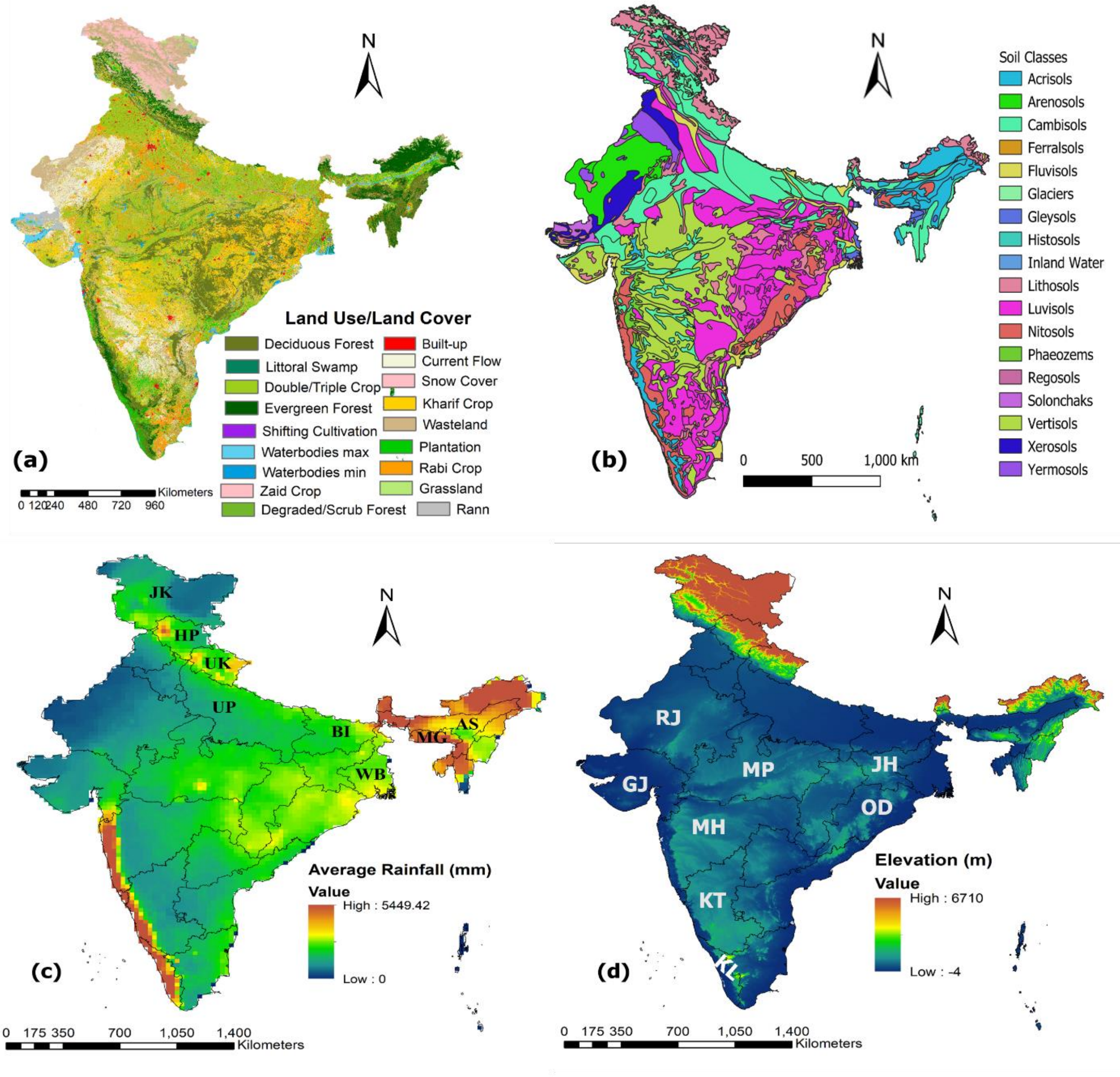

Figure1: Study area map showing LULC classes, soil classes, average rainfall, and topography reflecting elevations in (a), (b), (c) and (d) respectively.

2.2 Data sources

The RUSLE model was utilized in the development of the national-scale soil erosion and sediment yield maps over India. The soil erosion process consists of the impact of rainfall, soil properties, topographic conditions, and agricultural support practices. The initial two factors associated with rainfall and soil were extracted from (IRED and ISED) Indian Rainfall Erosivity and Erodibility Datasets. The factors associated with topographic and agricultural support practices (Topographic (LS), Cover Management (C) and Support Practice (P)) factors were estimated in this study using LULC and DEM (Digital Elevation Model). The flow accumulation and DEM datasets were employed for the computation of SY and SDR through utilization of the InVEST SDR model. Observed average yearly sediment load at unclassified gauge stations was extracted from Center Water Commission (CWC), India water yearbooks. Table 1 details the sources and spatial resolution of the used datasets in this research.

Table 1: Specifications of the datasets used in this study

Product	Full Name	Spatial Resolution	Format	Providing Agency
IRED	Indian Rainfall Erosivity Dataset	0.12 ° x 0.12 ° (~12 Km)	netcdf	https://zenodo.org/doi/10.5281/zenodo.6469693
ISED	Indian Soil Erodibility Dataset	250 m	netcdf	https://zenodo.org/doi/10.5281/zenodo.6505314
DEM	Digital Elevation Model	90 m	tiff	Multi-Error-Removed Improved-Terrain (MERIT) Hydro
LULC	Land use/Land cover	56 m	tiff	National Remote Sensing Center, Indian Remote Sensing Organization

2.2.1 Indian Rainfall Erosivity Dataset

Raj et al., (2022) represents the inaugural endeavor to conduct a comprehensive assessment of rainfall erosivity at a national scale across India. The accompanying Indian Rainfall Erosivity Dataset (IRED) from this publication has been harnessed for the purposes of this study. This dataset encompasses extensive long-term annual averages of critical parameters, including the R-factor, Fournier Index (FI), and Modified Fournier Index (MFI), on a nationwide basis. Within the context of the present study, the yearly mean rainfall erosivity (R-factor) map [Figure 2(a)] has been integrated as an input for the RUSLE model. This R-factor was derived using hourly IMDAA (Indian Monsoon Data Assimilation and Analysis) precipitation product for 40 years (01-01-1979 to 31-12-2018) and processed further using the principle of kinetic energy of rainfall intensity (Raj et al. (2022). The computed average R-factor for India stands at 1200 MJ-mm/ha/yr, registering a zenith of 23909.21 MJ-mm/ha/h/yr within the Laitknsew and Cherrapunji region of the East Khasi Hills in Meghalaya state, while reaching a nadir of 8.10 in the Shahi Kangri mountain region of Ladakh (Raj et al., 2022). Remarkably, they also revealed that the Kokrajhar district in Assam and the Meghalaya sub-division exhibit elevated vulnerability to rainfall erosivity, characterized by an average R-factor of 17972.38 MJ-mm/ha/h/yr, whereas Leh in Ladakh showcases the lowest vulnerability at 42.12 MJ-mm/ha/h/yr.

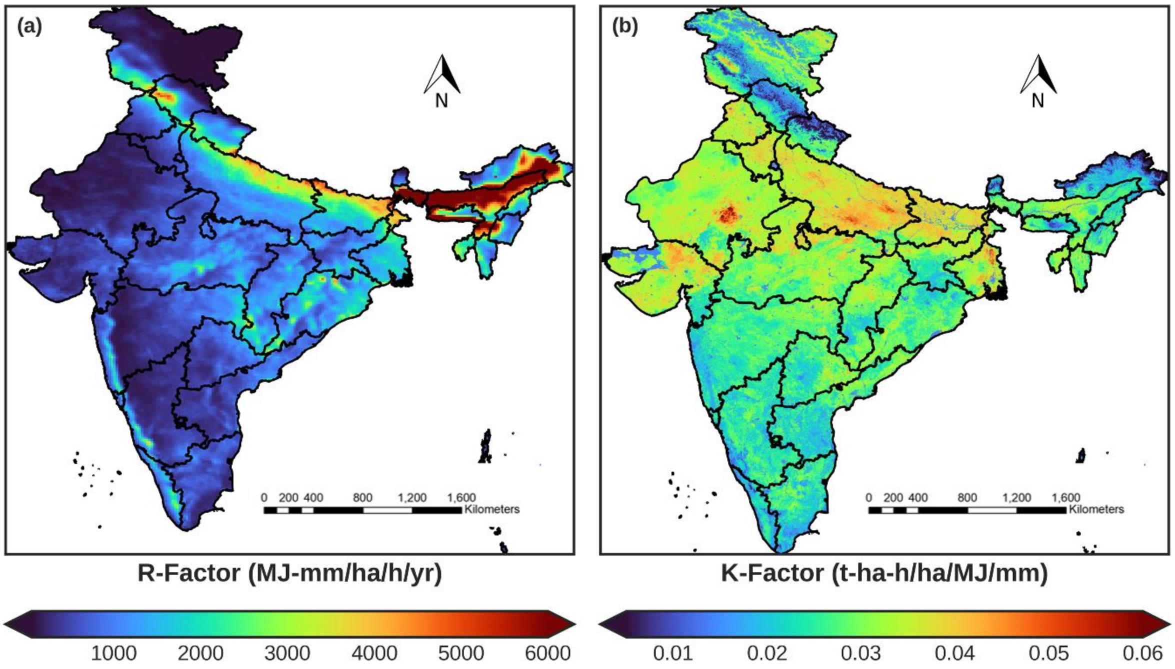

Figure 2: Maps depicting rainfall erosivity (a) and soil erodibility (b) across India (Raj et al., 2022 and Raj et al. 2023)

2.2.2 Indian Soil Erodibility Dataset

Soil erodibility is the capacity of soil to hold its particles against soil erosion induced by rainfall, runoff, and other means. The values of soil erodibility needed for the RUSLE model have been sourced from the ISED dataset (Raj et al., 2023), marking the novel national-scale mapping of soil erodibility over India [Figure 2(b)]. RUSLE's Nomograph model had been used to estimate K-factor for India using the percentage content of sand, silt, clay, percentage of soil organic matter (SOM), permeability, and structure code. The percentage content of sand, silt, clay and soil organic carbon (soc) were sourced from SoilGrids of ISRIC (International Soil Reference and Information Centre) (Hengl et al., 2017). Structure and permeability codes for India were derived considering texture classes which were estimated using the soil texture calculator developed by Natural Resources Conservation Service Soils (NRCS) of the United States Department of Agriculture (USDA) (Raj et al., 2023). This dataset encompasses K-factor (t-ha-h/ha/MJ/mm) values for India, along with associated soil erodibility indices such as CLOM (Critical Level of Organic Matter), Modified Clay Ratio (MCR), and CR (Clay Ratio) at a spatial resolution of 250 meters. Figure 2(b) visually presents the cartographic representation of soil erodibility across India, derived from the ISED repository. The calculated mean soil erodibility (K-factor) for India is recorded at 0.028 t-ha-h/ha/MJ/mm. The range of

K-factor values spanned from zero to 0.067 t-ha-h/ha/MJ/mm, with a mere 0.4% of values surpassing the threshold of 0.046 (Raj et al., 2023). They also revealed that the district of Anjaw in Arunachal Pradesh emerges as possessing the lowest vulnerability to soil erosion, whereas Ajmer in Rajasthan stands as the most susceptible district with a K-factor value of 0.034 t-ha-h/ha/MJ/mm. Notably, among the 631 districts in India, a total of 336 districts exhibited soil erodibility factors surpassing the national average K-factor value of 0.028 (Raj et al., 2023).

2.2.3 Topographic Data

Surface and elevation features of topography were extracted LULC and DEM datasets. Land use denotes the intended role or function of a specific land piece, considering activities like agriculture, preservation of wildlife habitat, or recreational works. Conversely, land cover delineates the physical attributes present on the land's surface, considering elements like vegetation, urban infrastructure, water bodies, and exposed soil. To effectively manage LULC data, it is necessary to have both proper mapping and ongoing monitoring of the land cover. This is because the latest information is required to determine what proportion of land is being used for different purposes and to identify changes in land use over time. Accurate identification, delineation, and land cover mapping are critical for global monitoring studies, resource management, and planning efforts. LULC data provides important information for understanding the current landscape. The LULC data for this study was borrowed privately with a resolution of 56 m and a scale ratio of 1:250000 from the National Remote Sensing Center, Indian Remote Sensing Organization (NRSC, ISRO). This LULC dataset is generated using Resourcesat 1, 2 2A - AWiFS (56m) and contains 18 different classes to visualize and differentiate each LULC class in India.

DEMs are used for mapping topography digitally that employs a grid of cells to represent a continuous topographic elevation surface. Each cell provides information on a feature's elevation (Z) in relation to its location coordinates (X and Y). This study utilized the Multi-Error-Removed Improved-Terrain (MERIT) DEM as an input to the RUSLE model, which was set up over India. The MERIT DEM (SRTM3 v2.1 and AW3D-30m v1) was produced by removing multiple error components, including absolute bias, stripe noise, speckle noise, and tree height bias, from the existing satellite based DEMs (Yamazaki et al., 2017). It spans the area bounded by 90 degrees north latitude and 60 degrees south latitude in relation to the EGM96 geoid model, providing a depiction of elevation data with a spatial resolution of 3 seconds (equivalent to 90 meters at the equator).

2.3 Methodology

The empirical RUSLE model was employed for the purpose of comprehensive mapping of soil erosion, and subsequently, SDR and SY were computed at the individual pixel level through the utilization of parameters related to upslope area and downslope length. The overall methodology of this study is depicted in Figure 3. Geographic Information System (GIS) tools and Python libraries were employed to process and visually present the datasets and resultant outcomes. The cumulative potential annual soil loss is the outcome of integrating all five constituent factors (**R** X **K** X **LS** X **C** X **P**) of the RUSLE model, accomplished at a comprehensive spatial resolution of 250 meters. A feature importance analysis was also performed with quantified soil loss and contributing factors to check which of the factors or combination of factors has greater influence on soil erosion process in India. The Potential Soil Loss (PSL) was further subjected to multiplication with the SDR to estimate sediment yield across the national perimeter. The pixel-scale estimation of SDR was conducted through the SDR module of the InVEST model. Additionally, a new erosion-severity classification system has been proposed to assess erosion and severity explaining its possible impact on agriculture and infrastructure considering literature recommendations (Aswathi et al., 2022; Belayneh et al., 2019; Seutloali et al., 2017; Zerihun et al., 2018).

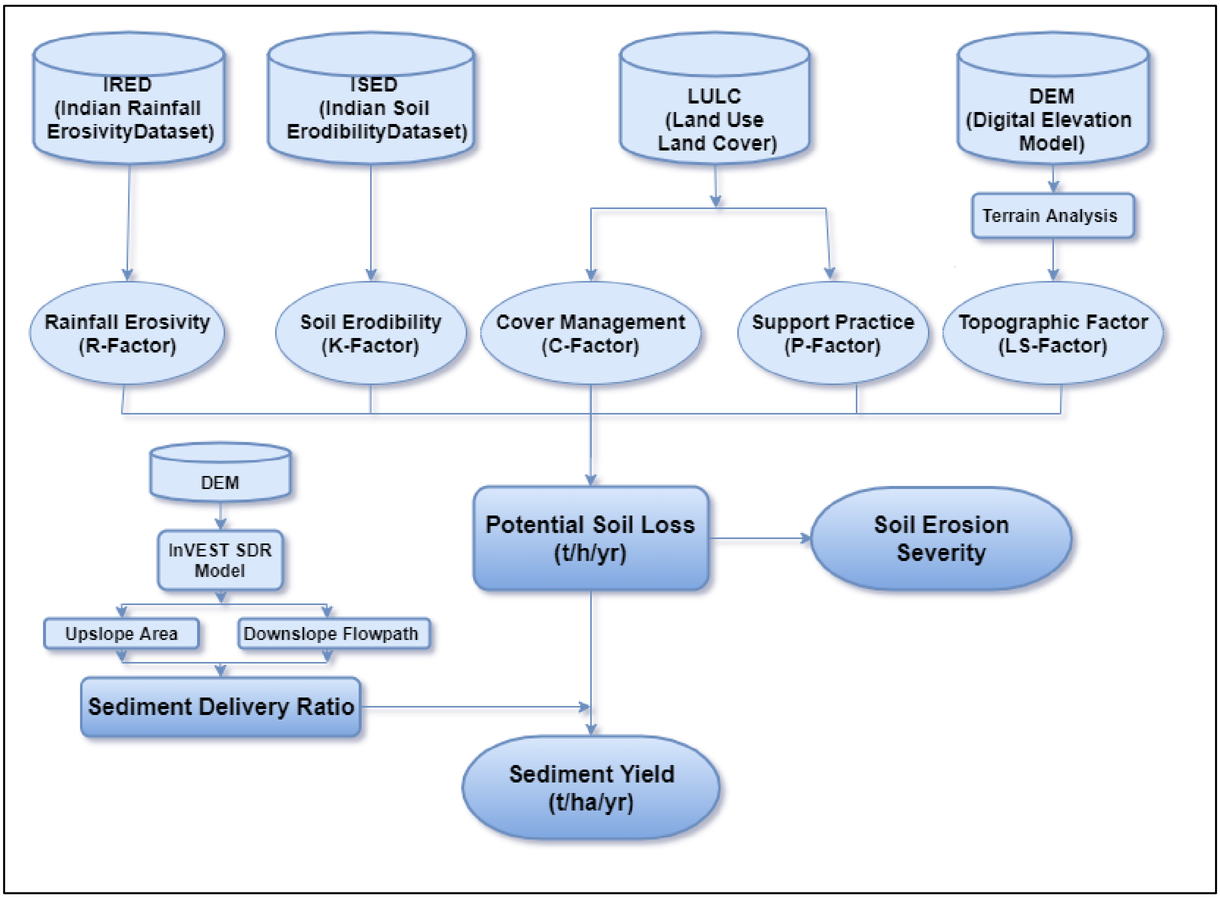

Figure 3: Methodology for soil erosion mapping over India

2.3.1 Topographic factor

The parameter representing the feature of land and slope length, often referred to as the topographic factor or LS-factor, accounts for the topography's influence on sheet and rill erosion. The S-factor quantifies the impact of slope steepness, while the L-factor quantifies the impact of slope length. The LS-factor generally depicts the relative soil erosion in comparison to the standard plot having a 9% of slope and 22.13 m length (Wischmeier and Smith, 1978). Various empirical methods utilizing GIS techniques are proposed for the estimation of the LS-factor. Hrabalíková and Janeček (2017) reported that the results of L-factor estimation using GIS and manual methods differed by approximately ten percent (McCool et al., 1997), while the S-factor estimates showed similar results. Desmet and Govers, (1996) employed the concept of the unit-contributing region to estimate LS-factor for a two-dimensional landscape, as explained in the following equations 1(a) to (c):

$$L_{i,j} = \frac{(A_{i,j-in} + D^2)^{m+1} - A_{i,j-in}^{m+1}}{D^{m+2} * x_{i,j}^{m} * 22.13^{m}} \tag{1(a)}$$

$$m = \frac{\beta}{\beta+1} \tag{1(b)}$$

$$\beta = \frac{\frac{\sin\theta}{0.0896}}{[0.56+3*(sin\theta)^{0.8}]} \tag{1(c)}$$

Where, $A_{i,j-in}$ = Contributing area for the inlet of the (i,j) grid cell in a m^2

$X_{i,j}$ = sin$a_{i,j}$ + cos$a_{i,j}$ with $a_{i,j}$ = Aspect Direction of the (i.j) grid cell

D = Size of the grid cell in m

m = 0 to 1, When rill to interrill erosion is near to 0, m approaches 0.

β = Ratio of rill to interrill erosion

θ = Slope angles (degrees)

They also demonstrated that this approach of calculating slope and steepness factor is suitable for catchment scale soil loss modeling by accounting for the complex nature of the topography. This study utilized the LS-factor module of the Q-GIS Terrain Analysis – Hydrology tool based on the algorithm proposed by Desmet and Govers(1996). This algorithm was incorporated by Panagos et al. (2015a) to map LS-factor for the European countries.

2.3.2 Cover Management factor

Cover management, also referred to as the C-factor, is a parameter that measures the impact of cropping and management techniques on erosion caused by water (Renard et al., 1997). The land and vegetation cover intercepts precipitation, reduces the kinetic energy of the precipitation, and increases infiltration. The estimation of C-factor relies on LULC, which was used for estimating the C-factor (Kaffas et al., 2021; Koirala et al., 2019; Tsegaye and Bharti, 2021). A high-resolution 1:250K (~56 m) LULC map developed by NRSC, ISRO (National Remote Sensing Centre, Indian Remote Sensing Organization) Hyderabad, India, had been processed in this study for assigning C-factor values across India at each grid cell considering literature recommendations (Ebabu et al., 2022; Kaffas et al., 2021; Maqsoom et al., 2020; Panagos et al., 2015b). The values of the cover management factor span a range from 0 to 0.45, depending upon the specific LULC classifications, which are shown in Table 2, along with their respective values. C-factors for most of the classes were directly borrowed from Ebabu et al. (2022) and Koirala et al. (2021). The Cropland class covers Kharif, Rabi, Zaid, and Shifting cultivation with a C-factor of 0.34. The Forest class covers Evergreen and Deciduous forests with a C-factor of 0.11, Shrubland with 0.11 covering Scrub and Littoral Swamp forest classes, Grassland with a C-factor of 0.16, and Plantation with a C-factor of 0.18. C-factors for the remaining three classes, i.e., Double/Triple, Current fellow, and Rann, were selected by considering recommendations made by Panagos et al. (2015) and Kaffas et al. (2021).

2.3.3 Support Practice Factor

The P-factor, or support practice factor, is a metric that compares the amount of soil lost due to a specific agricultural support practice to the amount of soil lost due to upslope cultivation and downslope cultivation (Tsegaye and Bharti, 2021; Wischmeier and Smith, 1978). The P-factor assumes a crucial role in the management of local soil erosion by mitigating the erosive influences of runoff and precipitation through its impact on flow patterns. In the absence of management practice data, the P factor is derived using Land Use and Land Cover data (Ebabu et al., 2022).

The values attributed to the P-factor for individual LULC categories span from 0 to 0.6, presented in Table 2. This table draws on recommendations from the literature (Ebabu et al., 2022; Kaffas et al., 2021; Maqsoom et al., 2020; Panagos et al., 2015b). P-factor for most of the classes are directly borrowed from the Ebabu et al., (2022). For forest classes and wastelands, it is assumed that the chances of agricultural support practices in these land use classes is very less, that is why P-factor for these classes were not factorized and considered as one. P factor values for forest LULC classes was used as 1 by Zerihun et al., (2018).

Table 2: The values associated with Cop management (C-factor) and Support Practice (P-factor) pertaining to the individual LULC classes

LULC Type	LULC Code	C-factor	P-factor
Build up	1	0	0
Kharif	2	0.34	0.49
Rabi	3	0.34	0.49

Zaid	4	0.34	0.49
Double/triple	5	0.32	0.49
Current fellow	6	0.38	1
Plantation/orchard	7	0.18	0.6
Evergreen forest	8	0.03	1
Deciduous forest	9	0.03	1
Scrub/deg forest	10	0.11	0.29
Littoral swamp	11	0.11	1
Grassland	12	0.16	0.41
Shifting cultivation	13	0.34	0.49
Wasteland	14	0.45	1
Rann	15	0.4	1
Water bodies max	16	0	0
Water bodies min	17	0	0
Snow Cover	18	0	0

2.3.4 RUSLE Model Set up

The product of all five factors was computed to derive the annual Potential Soil Loss (PSL) at a composite spatial resolution of 250 meters. The R-factor, borrowed initially at a spatial resolution of around 12 kilometers from IRED dataset, was subsequently resampled to a resolution of 250 meters, under the presumption of uniformity within the 12-kilometer grid area. The K-factor was acquired at a 250-meter resolution, the LS-factor was derived from the MERIT DEM featuring a 90-meter resolution, and the C and P factors were sourced from the ISRO’s LULC dataset at a resolution of 56 meters. To obtain a standard grid size for the final annual potential soil loss, these three datasets were also re-gridded to 250 m, and Equation 2 displays the results in t/ha/yr.

$$PSL = R * K * LS * C * P \qquad (2)$$

With, PSL = Potential Soil Loss in t/ha/yr

R = Rainfall erosivity factor in MJ-mm/ha/h/yr

K = Soil erodibility factor in t-ha-h/ha/MJ/mm

C = Cover management factor (Unitless)

LS = Topographic factor (Unitless)

P = Support practice factor (Unitless)

2.3.5 Sediment Delivery Ratio

The Sediment Delivery Ratio (SDR) denotes the watershed's capacity to transport soil particles from erosion-prone areas to the point where sediment yield is gauged and is often expressed as a ratio or percentage. For this study, the pixel-level SDR values across the investigated area were estimated using the SDR module within the Integrated Valuation of Environmental Services and Trade-offs (InVEST) model. The model calculates the Connection Index (CI) for each pixel, an approach originally outlined by (Borselli et al., 2008), which applicates the hydrological linkage between sediment origins (i.e., the topographical layout) and deposition areas (i.e., streams). Pixels with higher CI values indicate greater connectivity between the erosion source and sink. This condition occurs when there is less vegetation or a steeper slope. On the other hand, vegetated areas and gentle slopes are associated with lower scores, indicating weaker connectivity. Equation 3 can be used to calculate CI:

$$CI = log_{10} * (\frac{D_{up}}{D_{dn}}) \tag{3}$$

Where, CI = Connectivity Index

D_{up} = Upslope Area

D_{dn} = Downslope Flow path

The computation of the Connection Index (CI) hinges upon both the upslope area associated with each pixel and the pathway through which flow occurs from the pixel to the nearest channel. If the upslope region is extensive, with a mild slope and dense vegetative cover (resulting in a low USLE C factor), the sediment transport potential to the stream will be reduced. Similarly, if the downslope way between the stream and the pixel is long, with a gentle slope and dense vegetative cover, the distance between the pixel and the stream will be lower. Figure 4 illustrates the working mechanism of this model. The evaluation of SDR for a given pixel (i) is dependent on its upslope area and the downward trajectory. The module computes the specific values for D_{up} and D_{dn}. The quantification of sediment yield or the net soil loss at each individual pixel was executed by the product of the previously determined Potential Soil Loss (PSL) and the computed SDR.

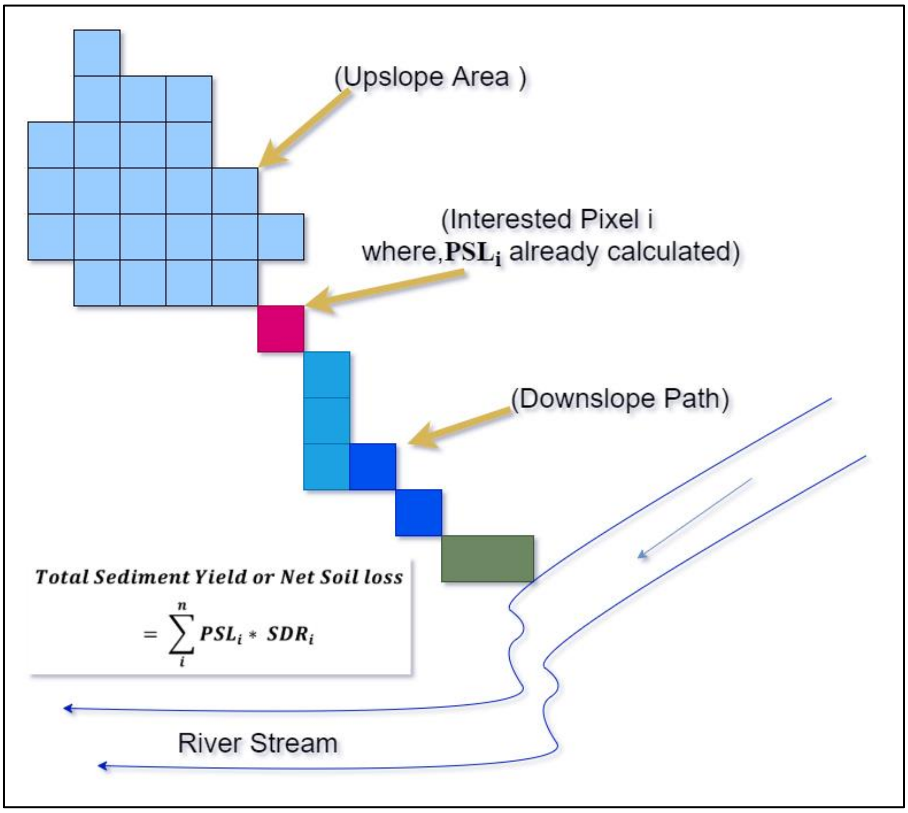

Figure 4: The working mechanism of InVEST Sediment Delivery Ration (SDR) model

2.3.6 Sediment Yield

The estimated soil erosion derived through the application of the RUSLE), denoted by the values of PSL at each pixel, does not completely carry over to the downstream pixel. Instead, only a fraction or portion of the PSL is transported. The net soil loss at each pixel or region is termed as Specific Sediment Yield (SSY) or Sediment Yield for that pixel or region. It can be calculated by multiplying PSL with SDR, as shown in Equation 4.

$$SSY = PSL * SDR \tag{4}$$

Where, SSY = Specific sediment yield or net soil loss in t/ha/yr

PSL = Potential soil loss in t/ha/yr

SDR = Sediment delivery ratio

2.3.7 Feature Importance Analysis

Feature importance of parameters based on the composite weight is a basic step in machine learning algorithms as it quantifies the most effective feature among the group of several parameters. This analysis is based on the Random Forest algorithm for machine learning model which is used for regression and classification tasks. Random Forest is a composite learning algorithm that builds several decision trees while training datasets and creating outputs of the individual trees. Feature importance is the built-in function of the Random Forest model and is measured with the help of the Gini impurity index which is also called the decrease in node impurity. In the first step of the analysis, the total decrement in the equivalent metric caused by an individual parameter is estimated for every decision tree within the Random Forest algorithm. In the second step, a stable number is provided by summing the importance of individual parameters of all the trees. The more reliable parameter has the higher importance score and vice versa.

3 Results and discussions

3.1 Computation of RUSLE components

As discussed in the earlier sections, LS, C and P factors were estimated in this study. The topographic or LS-factor was spatially mapped using the MERIT Digital Elevation Model (DEM) through the application of Q-GIS software, and the resulting map is shown in Figure 5(a). The illustrated map portrays a mean LS-factor value of 6.42, featuring a maximum of 4306.06 and minimum of 0.03, with a standard deviation of 17.84. Arrow marks in the legend part of the LS-factor map [Figure 5(a)] reflect that less than one and greater than eight values are shown using deep blue and deep red colors, respectively. These extreme values are rare in the study region. The C-factor was mapped using the LULC map having eighteen classes, and each class was assigned a value taking references with the help of the literature listed in Table 2. Figure 5(b), which depicts the C-factor map for India, was created by following these criteria. The values assigned to the C-factor vary between 0 and 0.45 for LULC classes such as built-up, snow, water, and wasteland, in alignment with literature-based guidelines as elaborated in Table 2. The upper and lower bounds for the P values were established as 1 and 0, respectively. The outcome of this analysis is shown in Figure 5(c). The mean cover management and Support practice factors for India were determined to be 0.24 and 0.64, respectively.

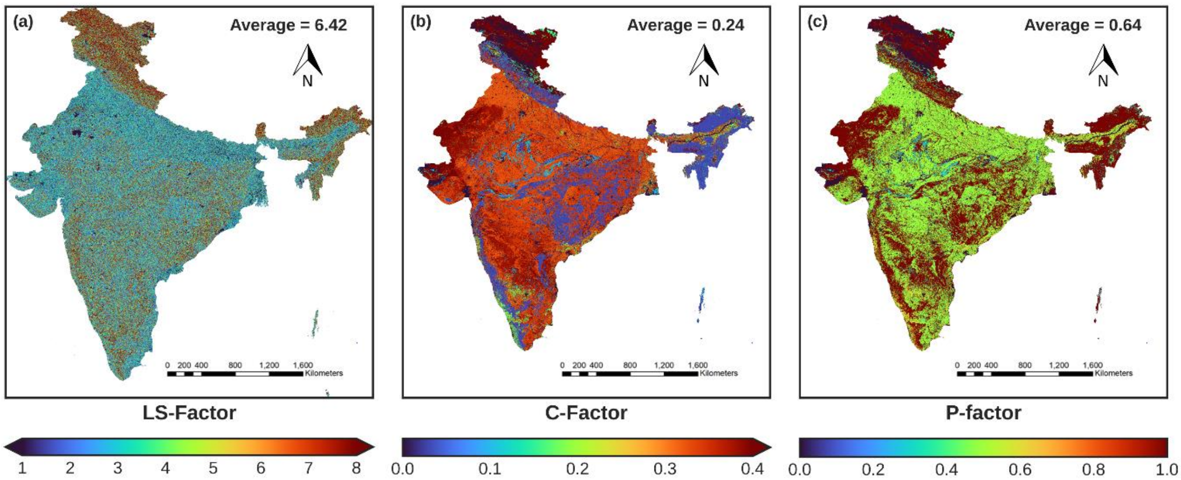

Figure 5: Maps illustrating the LS, C, and P factors of RUSLE across India, presented individually in (a), (b), and (c), with mean values displayed at the upper right corners

3.2 Soil Erosion Mapping

The RUSLE empirical formula was employed to assess the annual PSL in units of tons per hectare per year across the geographic extent of the study region. The map presenting the yearly mean soil erosion values in India is shown in Figure 6(a), with a national mean soil loss of 21 t/ha/yr. The yearly PSL values span a range from 0 to 52841.85 t/ha/yr, accompanied by a standard deviation of 81.27 t/ha/yr. The cumulative potential soil loss for India was computed to approximate 1195 million tons on yearly basis. However, the distribution of soil loss was not uniform across the country, as evident from the figure and PSL ranges. Therefore, we performed several analyses based on district, basin, soil texture and type, LULC class, and slope to understand the variability at varying scales.

Moreover, a comparative analysis was conducted between the PSL values and the R, K, C, P and LS-factors. This examination involved the extraction of 5000000 random points from each parameter to make a .csv file, followed by the computation of Pearson's Correlation Coefficient to quantify the degree of correlation. The highest correlation coefficient of 0.42 was observed for LS factors with PSL values followed by 0.32 for R-factor and 0.28 for C-factor with potential soil loss values in Indian condition. These results suggest that none of the RUSLE factors are highly correlated with annual potential soil loss values in the Indian context. Further, a feature importance analysis was also performed between RUSLE contributing factors and PSL values to check which parameter has greater influence in estimating soil loss in Indian condition.

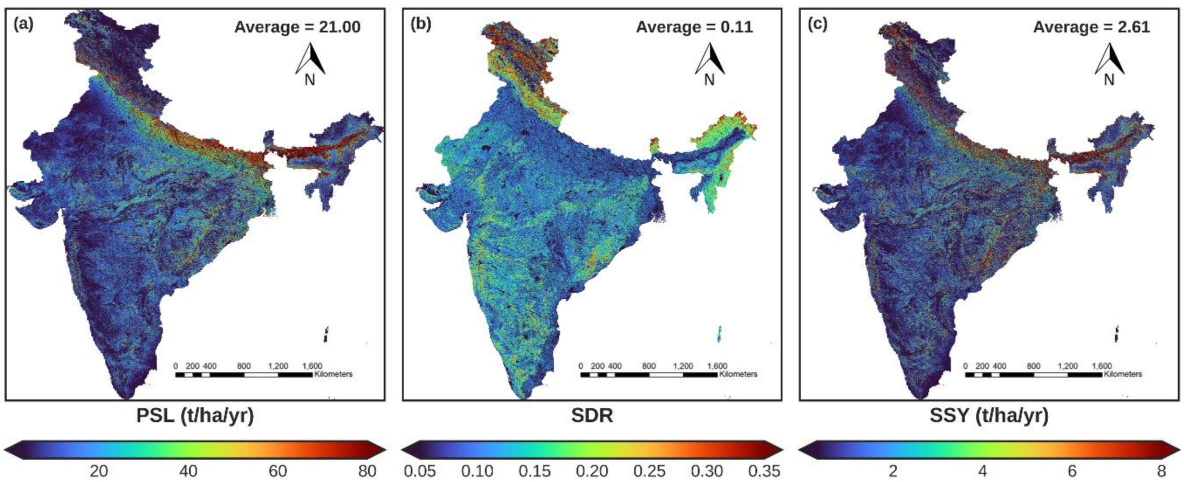

Figure 6: National-level maps illustrating Annual PSL (Potential Soil Loss), SDR (Sediment Delivery Ratio), and SSY (Specific Sediment Yield) at a consolidated resolution of 250 meters, with mean values indicated in the upper right corners for sections (a), (b), and (c) correspondingly.

The simulated PSL map for the study region was compared with the Global soil displacement map for croplands by Borrelli et al. (2022). A Pearson correlation coefficient of 0.47 was obtained by comparing the district average simulated potential soil erosion values with the global soil erosion modeling (GloSEM) values. This could be due to the difference in the data sources used and the different time durations to calculate soil loss using both methods. The GloSEM study took the rainfall erosivity factor from Panagos et al. (2017), which considered an average of seven years of precipitation datasets, while Raj et al., (2022) used 40 years of rainfall datasets to estimate rainfall erosivity over India, which has been used in this study as mentioned by Vantas et al., (2019), a minimum of 20 years rainfall records is required to estimate long-term rainfall erosivity factor. Unlike the GloSEM study, the LULC datasets utilized in this research were sourced from NRSC, ISRO, which constitutes a nationally unavailable dataset at a high resolution, utilized for estimating C and P factors. This distinction potentially contributed to the observed correlation coefficient of 0.47. The average annual national average for croplands using GloSEM and the current studies were recorded as 16.84 and 22.73 t/ha/yr, respectively, which are comparable.

To check the reliability of the simulated PSL values, regional or sub-watershed scale studies from the literature were used for validation. Prasannakumar et al. (2012) estimated potential soil losses in the span of 0 to 17.73 t/ha/yr over a small catchment in the Pamba river basin, which covers the Pathanamthitta district of Kerala (a southern state of India, Figure 1(d)), which is comparable to the simulated average annual potential soil loss of 11.51 t/ha/yr. Dabral et al. (2008) estimated the average annual soil loss as 51 t/ha/yr, which falls in the Papum Pare and Lakhimpur districts of Arunachal Pradesh and Assam states, respectively, having simulated PSL values of 32.02 and 77.35 t/ha/yr with an average of 54.68 t/ha/yr potential soil loss value, which is also comparable. Biswas and Pani (2015) estimated the yearly mean soil loss in the Barakar river basin of Jharkhand and observed that 80% of the values are less than 14 t/ha/yr, which is comparable to the simulated average annual potential soil loss of 18 t/ha/yr.

Out of 630 districts, about 266 districts have an annual PSL greater than the national average PSL of 21 ton per hectare per year. According to the mean annual PSL values, nine of the twenty most erodible districts are located in Assam, three in Meghalaya, Himachal Pradesh, and Jammu-Kashmir, and two in West Bengal. Table 3 shows the mean annual PSL values in tons and total potential soil loss in a million tons each year for these 20 districts. The prevailing soil texture classes in the states of Assam and Meghalaya are predominantly loamy, clay loamy, silt loamy, and sandy clay loamy. These soil types exhibit insufficient resistance to water-induced soil erosion. Additionally, a significant proportion of these regions are characterized by slopes, necessitating improved soil conservation measures. These districts of Assam and Meghalaya also exhibit some of the highest values of rainfall erosivity (Raj et al., 2022), which is a significant contributor to potential soil erosion.

Table 3: Top 20 most vulnerable districts of India corresponding to Higher mean annual PSL

Districts	State	Mean Annual PSL (t/ha/yr)	Total Soil Loss (M-t/yr)
Chirang	Assam	201.99	6.11
Baksa	Assam	193.18	8.21
Kokrajhar	Assam	174.70	9.46
East Khasi Hills	Meghalaya	164.52	8.16
Bongaigaon	Assam	155.68	2.94
Dhubri	Assam	146.51	5.95
Barpeta	Assam	138.20	5.72
Rajouri	Jammu & Kashmir	122.99	4.56
Udalguri	Assam	118.43	4.16
Koch Bihar	West Bengal	113.36	5.82
Jaintia Hills	Meghalaya	112.73	7.58
Goalpara	Assam	107.19	3.86
Nalbari	Assam	105.28	1.95
South Garo Hills	Meghalaya	104.49	3.47
Punch	Jammu & Kashmir	100.83	4.66
Mandi	Himachal Pradesh	98.33	7.33
Sirmaur	Himachal Pradesh	93.13	4.89
Kangra	Himachal Pradesh	91.84	9.95
Jalpaiguri	West Bengal	88.82	9.48
Reasi	Jammu & Kashmir	88.69	3.88

3.2.1 Soil-based Analysis

In this part, a soil-based analysis was conducted to visualize the spatial variability of possible soil losses corresponding to the soil classes and textures. Six of India's 18 soil classes

(Gleysols, Regosols, Acrisols, Cambisols, Fluvisols, and Nitosols) have higher average potential soil losses than the national average PSL, i.e., (21 t/ha/yr), accounting for approximately 35% of the geological area. Gleysols and Regosols soil classes are less than 2% of the area, having 53.52 and 41.88 t/ha/yr potential soil losses because of their lower resisting forces against water erosion. Gleysols are formed in saturated conditions caused by rising groundwater levels, while Regosols have shallow and unconsolidated parent material that may be alluvial and have no soil horizon (layer) due to dry or cold climates. Such characteristics of these two soil classes might be responsible for such higher PSL values over the national boundary. The Luvisols class, generally formed in nearly to gently sloped landscape that covers the largest proportion of the country (22.21% area), has average PSL values of 20.05 t/ha/year. A detailed analysis of all the soil classes with their mean annual PSL values has been shown in Table 4.

Table 4: Average potential soil erosion corresponding to the soil classes over India

Soil Class	Mean Potential Soil Loss (t/ha/yr)	Area (%)
Luvisols	20.05	22.211
Vertisols	14.44	18.130
Cambisols	30.80	17.874
Lithosols	17.37	11.647
Nitosols	23.69	6.613
Acrisols	37.08	5.970
Arenosols	6.82	4.991
Fluvisols	24.79	3.127
Xerosols	10.64	2.867
Yermosols	5.53	1.556
Glaciers	7.40	1.480
Regosols	41.88	1.240
Solonchaks	7.52	0.811
Gleysols	53.52	0.733
Phaeozems	9.54	0.528
Inland Water	16.00	0.218
Histosols	0.67	0.003
Ferralsols	1.43	0.003

The annual potential soil loss values were extracted as per major soil texture classes according to NBSS LUP classifications to visualize its variation. Only the loamy texture class, which comprises about 46.03 percent of India, has a higher average PSL value (26.17 t/ha/yr) than the national average PSL value (21 t/ha/yr). Loamy soil comprises an adequate amount of sand, silt, and clay, which makes agricultural practices easier and exposes it to higher water erosion. A detailed explanation of other soil texture classes has been shown in Table 5. About 18.23 and 13.81 t/ha/yr average soil loss values were recorded for Clayey and Sandy texture classes, respectively.

Table 5: Average potential soil losses for soil texture classes defined by NBSS-LUP

Texture Class	Mean PSL (t/ha/yr)	Area (%)
Loamy	26.17	46.034
Clayey	18.23	32.388
Sandy	13.81	10.791
Rock outcrops	14.95	5.755
Glaciers & Rock outcrops	8.85	2.15
Waterbodies	23.70	1.566
Rock mountains	12.34	0.727
Rann of Kutch	6.66	0.546
Miscellaneous	24.04	0.042

3.2.2 Basin-scale analysis

There are majorly 21 basins in India, according to India-WRIS (Water Resources Information System). An analysis was also performed to visualize the variation of potential soil losses among it, which is shown in Table 6. The study revealed that the Brahmaputra basin (covers mostly the northeastern part) has the potential to experience the highest annual soil loss, estimated at 47.64 tons per hectare per year. This is succeeded by the East Flowing Mahanadi basin, anticipated to encounter 28.42 tons per hectare per year, and the Ganga (covers mostly northern part) basin, which could undergo 25.07 tons per hectare per year of soil loss. The Non-Indus basin was observed to experience the least soil losses at 3.22 t/ha/yr. Five out of twenty-three basins have annual potential soil losses greater than the national average soil loss. The main reason for higher PSL values in Brahmaputra and Ganga basin is due to the new soil layer formation every year due to flooded water. This new soil layer has very less capacity to withstand erosive forces raised due to rainfall and runoff.

Table 6: Average potential soil losses corresponding to basins of India

Sr No	Basin	Area (%)	Mean PSL (t/ha/yr)
1	Brahmaputra	8.33	47.64
2	East Flowing Mahanadi	1.67	28.42
3	Ganga	26.39	25.07
4	Subarnarekha	2.47	24.10
5	Mahanadi	4.10	23.45
6	Indus	15.01	19.38
7	Narmada	2.93	18.47
8	Mahi	1.28	17.99

9	Godavari	9.29	17.32
10	Pennar	1.60	14.01
11	Cauvery	2.26	12.80
12	West flowing	3.22	12.53
13	Sabarmati	0.92	12.27
14	East Flowing Krishna	0.72	12.02
15	East Flowing Godavari	0.38	12.01
16	Ponnaiyar	1.82	11.68
17	Krishna	7.62	10.92
18	West Kachchh	5.80	10.30
19	Tapi	2.01	10.14
20	East Flowing Cauvery	1.26	6.49
21	Non-Indus	0.91	3.22

3.2.3 LULC-wise Analysis

To describe the variation in annual soil erosion, the major LULC types were assessed along with PSL values. These include agriculture (LULC codes 2,3,4,5,6,7 and 13), forest (LULC codes 8,9,10, and 11), grassland (LULC code 12), and barren/ran (LULC codes 14 and 15) (as outlined in Table 2). Agricultural land use comprises the Kharif crop, Zaid crop, Rabi crop, double/triple crop, current fallow, plantation, and shifting cultivation lands, whereas the forest class encompasses littoral swamp, evergreen, deciduous, and degraded types of forests. Of the various land types, barren land and agricultural class were estimated to be the most vulnerable to soil loss, with mean PSL values of 35.107 and 23.458 t/ha/yr, respectively (as shown in Table 7). In contrast, grassland was the least impacted by soil erosion, with a mean PSL value of 11.401 ton per hectare per year. Table 7 also reflects that grass cover provides greater stability against rainfall and runoff forces, which is one of the main reasons to showing least PSL values.

Table 7: Average potential soil losses corresponding to major LULC categories over India

LULC Category	Mean PSL (t/ha/yr)	Area (%)
Grass	10.401	0.841
Forest	14.396	25.46
Agriculture	23.458	59.98
Barren Land	35.107	13.71

3.2.4 Slope-wise Analysis

The geographical area of India was divided into seven slope categories defined by FAO classifications (Food and Agriculture Organization of the United Nations., 2006; Lele and

Goswami, 2021). Table 8 shows the mean PSL per year and each slope class's percentage of the covered area. Gentle to moderate slope areas (1 to 30 degrees) were observed to have mean PSL values higher than the national average PSL value of 21 t/ha/yr. This is because these areas typically have loamy soil, which is more susceptible to erosion as the low binding forces of this soil type, and additionally, gentle slopes provide a favorable condition to erode soil particles easily.

The flat or nearly level slope category, encompassing 48.43% of the nation's geographical expanse, exhibited a mean potential soil loss of 19.02 t/ha/yr. On the other hand, very steep and steep slope classes with slopes greater than 30 degrees were less affected by soil losses having mean PSL values of 10.49 and 17.53 t/ha/yr, respectively. Despite having higher slopes, the lower PSL values could indicate the effect of other associated factors to soil erosion, like soil types and texture. Higher slopy areas are generally found in mountainous regions with lower soil erodibility, leading to lower soil erosion.

Table 8: Average potential soil losses corresponding to major slope classes over India

Slope Range (Degree)	Slope Class	Mean PSL (t/ha/yr)	Area (%)
0-1	Flat / Near Level	19.02	48.43
1 to 5	Gentle Sloping	22.77	27.9
5 to 10	Sloping	23.83	6.06
10 to 15	Strongly Sloping	25.44	3.95
15-30	Moderately Steep	24.17	8.88
30-60	Steep	17.53	4.73
>60	Very Steep	10.49	0.05

3.2.5 Severity to Soil Erosion Analysis

Soil erosion severity classification system was prepared considering the past erosion classes recommendations proposed by various researchers (Aswathi et al., 2022; Belayneh et al., 2019; Seutloali et al., 2017; Zerihun et al., 2018). The motivation behind this classification system is to address regional variability in defining severity classes by incorporating the impact of specific soil loss (t/ha/yr) ranges on the formation of different erosion types, such as sheet, rill, gully, and deep gully shapes. Literature (Seutloali et al., 2017; Zerihun et al., 2018) suggests that a particular type of erosion (sheet, rill, gully, and deep gully) produces a range of soil loss (t/ha/yr). Seutloali et al. (2017) mentioned different severity classes reflecting corresponding erosion types, while Zerihun et al. (2018) highlighted those severity classes with quantified soil loss values (t/ha/yr). By considering these literature recommendations, we developed this new severity classification, where each class represents a specific erosion type, irrespective of regional variations. For example, sheet erosion can result in a range of 0-5 t/ha/yr, rill erosion can produce a range of 5 to 15 t/ha/yr, gully erosion can lead to 15-30, medium gully can result in 30-50, and deep gully can produce greater than 50 t/ha/yr. These statistics are independent of regional variability because erosion types create an impact on the landscape by forming sheet, rill, and gully shapes depending on the extent of soil loss (t/ha/yr) due to rainfall and runoff. We added one more class, i.e., catastrophic erosion (PSL > 100 t/ha/yr), considering its potential worst impact on agriculture and infrastructure. The proposed classification is presented in Table 9 highlighting the possible impact of erosion on agriculture and infrastructure. According to the literature, up to 5 t/ha/yr potential soil erosion could be categorized as E1 with minimal impact on farming and agricultural productivity.

Table 9: Categories of erosion severity and their effects on agriculture and infrastructure

Annual Soil Loss (t/ha/yr)	Erosion-Severity Class	Severity Code	Possible Impact	Area (%)
0 to 5	Minor Erosion	E1	Minimal Erosion	29.46
5 to 15	Moderate Erosion	E2	Possible risk to soil nutrients and agricultural output	29.11
15 to 30	Major Erosion	E3	Immediate harm to the most fertile land and agricultural output	15.49
30 to 50	Serious Erosion	E4	Significant reductions in agricultural productivity and potential limitations on land utilization	7.49
50 to 100	Severe Erosion	E5	Constrains land utilization and poses risks to roads and fencing	5.67
>100	Catastrophic Erosion	E6	Extensive destruction of roads, fences, and potential harm to structures	3.17

The catastrophic erosion class was introduced to account for its maximum impact on infrastructure such as roads, fences, and even buildings. This type of erosion often creates deep gullies, which could lead to the damage of roads and buildings. This classification was used to map the severity caused by erosion over the study region, which is shown in Figure 7. Soil erosion greater than 15 t/h/yr had various impacts, including potential damage to agricultural productivity and even harm to roads and fences, covering about 32% of the study region. Approximately 5% of the nation's geographical area, primarily covering the majority of Assam, along with some portions of Meghalaya and Himachal Pradesh, is falling in the E6 (Catastrophic) erosion class, denoting PSL values greater than 100 t/ha/yr, reflecting the possible severity to damage roads, fences, and buildings.

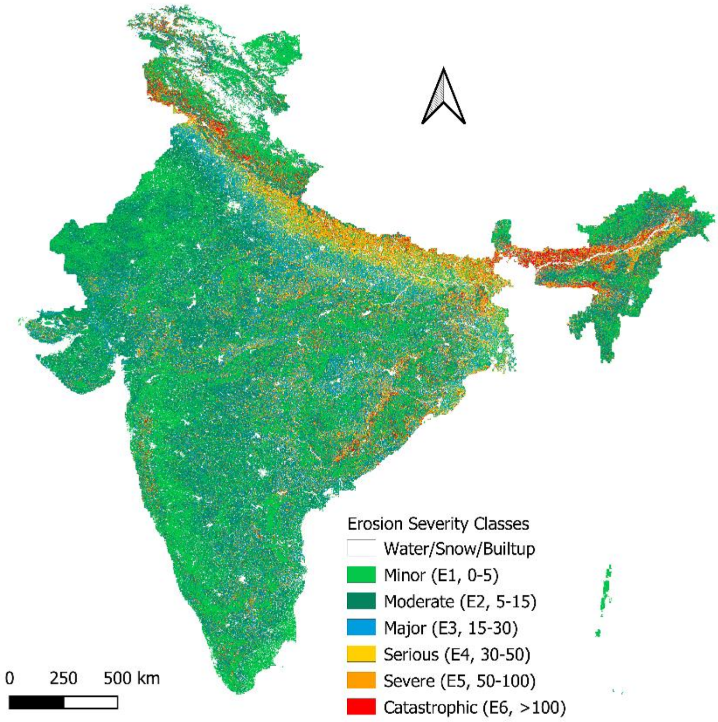

Figure 7: Mapping of Erosion-Severity classes over India

An analysis was conducted to visualize the variation of erosion-severity classes (E1-E6) for each LULC class, focusing on agriculture. The total LULC classes were divided into ten major sub-classes (Kharif crop, Zaid crop, Rabi crop, double/triple crop, current fallow, shifting cultivation, plantation, Grassland, Barren land, and Forest). The heatmap in Figure 8 shows the LULC areas in million hectares (Mha) covered by each severity class. Around 111 million hectares of LULC area is falling between E3 and E6 severity classes, indicating that these areas are directly affected by soil erosion in terms of agricultural productivity. In their study, Panagos et al. (2018) stated that agricultural land experiencing soil erosion more than 11 t/ha/yr may suffer a productivity loss of around 8%. Based on this recommendation and the erosion severity classes, it can be concluded that more than 78 million hectares of farmland lose an average of 8% of their yearly productivity due to the E3 through E6 severity classes in India. Figure 8 provides a detailed view of the percentage area of every erosion severity class with corresponding LULC class.

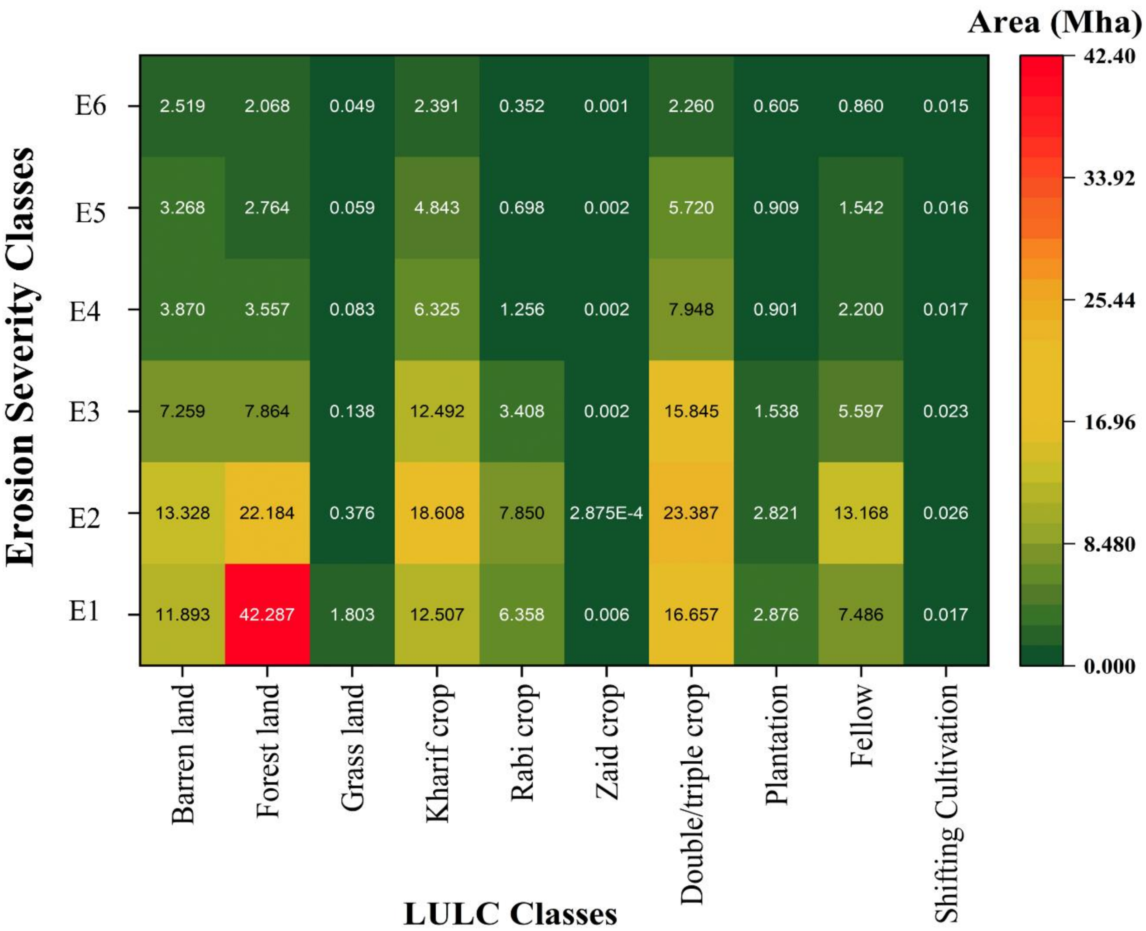

Figure 8: Distribution of land use areas for Erosion severity classes for major LULC types focused on agriculture

3.2.6 Feature Importance Analysis

The importance of parameters associated with the soil erosion process was necessary to visualize which of the contributing factor or parameter or set of parameters are influencing the soil erosion phenomena in the study region. All the five factors of RUSLE and the quantified soil loss (t/ha/yr) was analyzed using the Random Forest algorithm in machine learning to check the importance of associated features.

R-factor stands out as the most crucial feature in estimating soil erosion in Indian conditions when assessing the relevance of RUSLE factors to quantified soil loss (t/ha/yr). The LS factor follows, with C and K factors succeeding in importance. The combined impact of these factors was also analyzed using the Feature Importance module of Random Forest in machine learning. Rainfall intensity, combined with the topographic factor, demonstrates the highest influence on soil erosion. This suggests that areas with higher rainfall erosivity and steeper slopes are more prone to soil erosion. Although the impact of soil properties is ranked fourth when analyzed individually, the combined effect of soil erodibility with cover management emerges as the second most important feature. This implies that if the soil has a lower capacity to resist erosion, and the land use/land cover lacks grasslands or vegetation, it will accelerate the erosion process.

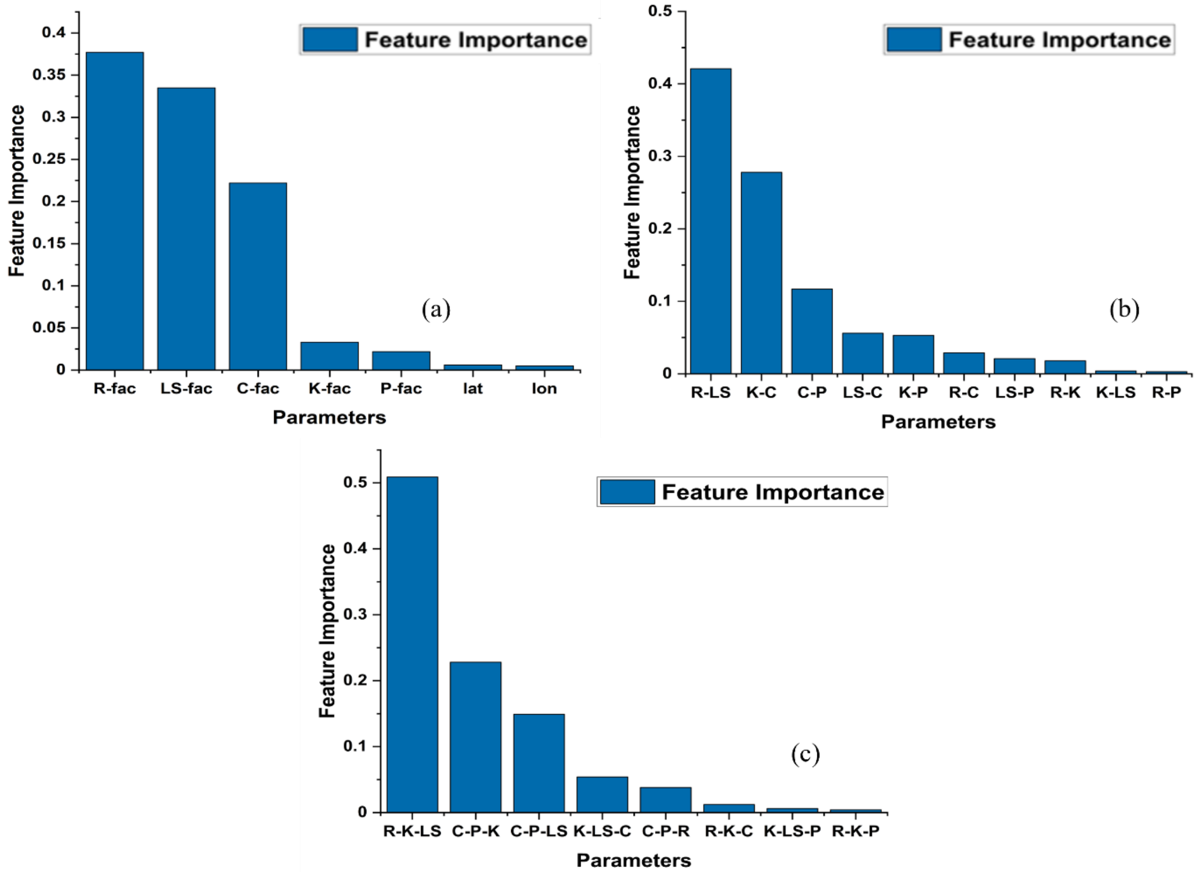

Figure 9: Feature importance of RUSLE factors versus potential soil loss is shown individually in (a), combined in pairs in (b), and grouped in threes in (c).

In order to further assess the combined impact of associated RUSLE factors on quantified soil loss (t/ha/yr), a set of eight combined factors, grouping three together, has been analyzed using the same Random Forest algorithm. The results show that rainfall erosivity with soil erodibility and topographic factors has the highest influence on the soil erosion process in Indian conditions. Additionally, the importance of soil properties, cover management, and agricultural practices emerges as the second most crucial combined features. This implies that despite higher rainfall intensity, the extent of soil loss could be minimized by conserving land cover and implementing agricultural support practices for soil management.

3.3 Sediment Yield Mapping

In this research, the InVEST SDR module was employed to generate a map showing sediment delivery ratios over India, visualized in Figure 6(b), encompassing values from 0 to 0.79, and presenting a national mean of 0.11. Notable higher sediment delivery ratio figures were observed in the upper regions of Jammu and Kashmir, Sikkim, Himachal Pradesh, and Arunachal Pradesh, as highlighted in Figure 6(b).

The multiplication of SDR by potential soil loss provides sediment yield or net soil loss at the pixel level. The outcome of this computation, SSY, is shown in Figure 6(c), displaying a range of 0 to 22528.54 tons per hectare per year, with an average of 2.61 tons per hectare per year on a national scale. As with PSL and SDR maps, the variation of SSY values is not uniform throughout the study region. Higher SSY values were found in the states of Assam (AS), West Bengal (WB), Bihar (BR), Uttar Pradesh (UP), Himachal Pradesh (HP), Uttarakhand (UK), and some portions of Meghalaya (MG) and Jammu & Kashmir (JK) which can be visualized by taking reference from Figure 1(c). Gauge-scale sediment yield was also estimated to compare our sediment yield map at the basin/gauge scale.

The yearly mean sediment load at gauge stations was observed and extracted from literature sources and the Center Water Commission water yearbooks. Additionally, the watersheds of these gauge basins were delineated using GIS. The total sediment load or net soil loss was estimated by adding values of all the pixels within the specific gauge watershed boundaries. A total of 108-gauge stations were used for validation, revealing that the simulated results consistently underestimated the yield at most stations. There were a few cases where the results were comparable. This suggests that relying solely on landscape soil erosion is insufficient for estimating sediment yield for Indian gauge stations. It is likely that a significant portion of sediment comes from riverine erosion, encompassing riverbed and bank erosion, as well as by-products of landslides. As RUSLE model itself does not account for gully erosion directly only its indirect impact is considered in the LS factor estimation. This could be also a reason of the underestimation of simulated sediment yield in this study. The observed average annual sediment loads, both observed and calculated, are detailed in Table S1 of the supplementary material Supplementary_S1 (available in the .xlsx file).

4 Conclusions and Future Work

This research attempts to model and map potential and net soil erosion at a high-resolution (250 m) over India. The factors of RUSLE, such as cover management, topographic, and support practice factors, were mapped in this study to create a national scale model of soil erosion along with estimates of SSY, SDR, and Soil Erosion Severity classification. A comparison of RUSLE factors with quantified soil loss was also performed to check the importance of individual and combined impact of associates parameters on soil erosion in Indian condition. This research work complements the national-scale rainfall erosivity and soil erodibility studies by Raj et al., (2023, 2022) in an attempt in developing a comprehensive understanding of soil loss in India. The following are the key findings of this study:

- The yearly potential soil loss for India is calculated at 21 t/ha/yr, with a total possible loss of 1408 million tons annually.
- Nine out of the twenty districts with the highest susceptibility to soil erosion are in Assam, with three in Meghalaya, three in Himachal Pradesh, three in Jammu-Kashmir, and two in West Bengal.
- Only the loamy texture class, which covers 46.03% of India, has a higher average PSL value (26.17 t/ha/yr) than the national average (21 t/ha/yr).
- The Brahmaputra basin has the maximum potential soil erosion of 47.64 t/ha/yr, followed by the East Flowing Mahanadi with 28.42 t/ha/yr and the Ganga basin with 25.07 t/ha/yr.
- Approximately 5% of the nation's geographical area, covering significant portions of Assam, some portions of Meghalaya, and Himachal Pradesh, was classified under E6 (Catastrophic) erosion category, with mean PSL values greater than 100 t/ha/yr. This (E6) class has potential to damage roads, fences and even buildings by creating deep gullies.
- More than 78 million hectares of agricultural land in India experience an average productivity loss of eight percent.
- Rainfall erosivity (R-factor) emerges as the most crucial feature in estimating soil erosion in Indian conditions. Additionally, when the combined impact was assessed, rainfall intensity, combined with the topographic factor, demonstrated the highest influence on soil erosion.
- The national mean values for SDR and SSY stand at 0.11 and 2.61 t/ha/yr, respectively. Furthermore, it is also concluded that relying solely on landscape-based soil erosion is insufficient for estimating sediment yield for Indian gauge stations.

This study represents the first such assessment of soil erosion and sediment yield over India at higher spatial resolution (250 m), which is a significant step towards developing a comprehensive understanding of soil erosion within one of the most adversely affected regions globally. In this study, it was assumed that rainfall erosivity would be uniform in the specified resolution of 12.4 km, given that the resulting map has a spatial resolution of 250 m. This assumption was based on the R-factor map borrowed from the IRED, which used IMDA precipitation data with a spatial resolution of 12.4 km. Since ground-based agricultural support practices data were not available for India, LULC-based recommendations were used to estimate C and P factors. However, this approach could be enhanced by incorporating ground-based records. As extensive local ground measurements were unavailable for this study, national and global gridded datasets were utilized. Nevertheless, these datasets have limitations depending on the statistical approaches used to interpolate spatial point values from ground measurements. To improve the accuracy of factors associated with soil erosion estimates, future studies could benefit from the availability of local ground-based observations at higher spatial resolutions. By incorporating more precise and comprehensive data, we can overcome the limitations of gridded datasets and obtain more accurate estimates of soil loss.

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Compliance with Ethical Standards

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

Ravi Raj: Data acquisition and processing, Methodology, Writing - Original draft preparation

Manabendra Saharia: Conceptualization, Writing - Review & Editing

Sumedha Chakma: Writing - Reviewing

Data Availability

The datasets employed in this study will be made accessible through the following link subsequent to the article's acceptance: https://doi.org/10.5281/zenodo.7823909

References

Asheghi, R., Hosseini, S.A., 2020. Prediction of bed load sediments using different artificial neural network models. Frontiers of Structural and Civil Engineering 1–13.

Aswathi, J., Sajinkumar, K.S., Rajaneesh, A., Oommen, T., Bouali, E.H., Binoj Kumar, R.B., Rani, V.R., Thomas, J., Thrivikramji, K.P., Ajin, R.S., Abioui, M., Sajinkumar, K.S., Ajin, R.S., Abioui, M., 2022. Furthering the precision of RUSLE soil erosion with PSInSAR data: an innovative model. Geocarto Int. https://doi.org/10.1080/10106049.2022.2105407

Balasubramani, K., Veena, M., Kumaraswamy, K., Saravanabavan, V., 2015. Estimation of soil erosion in a semi-arid watershed of Tamil Nadu (India) using revised universal soil loss equation (rusle) model through GIS. Model Earth Syst Environ 1, 1–17.

Beasley, D.B., Huggins, L.F., Monke, ampEJ, 1980. ANSWERS: A model for watershed planning. Transactions of the ASAE 23, 938–944.

Belayneh, M., Yirgu, T., Tsegaye, D., 2019. Potential soil erosion estimation and area prioritization for better conservation planning in Gumara watershed using RUSLE and GIS techniques'. Environmental Systems Research 8. https://doi.org/10.1186/s40068-019-0149-x

Bhattacharyya, R., Ghosh, B.N., Mishra, P.K., Mandal, B., Rao, C.S., Sarkar, D., Das, K., Anil, K.S., Lalitha, M., Hati, K.M., 2015. Soil degradation in India: Challenges and potential solutions. Sustainability 7, 3528–3570.

Biswas, S.S., Pani, P., 2015. Estimation of soil erosion using RUSLE and GIS techniques: a case study of Barakar River basin, Jharkhand, India. Model Earth Syst Environ 1. https://doi.org/10.1007/s40808-015-0040-3

Borrelli, P., Alewell, C., Alvarez, P., Anache, J.A.A., Baartman, J., Ballabio, C., Bezak, N., Biddoccu, M., Cerdà, A., Chalise, D., Chen, S., Chen, W., de Girolamo, A.M., Gessesse, G.D., Deumlich, D., Diodato, N., Efthimiou, N., Erpul, G., Fiener, P., Freppaz, M., Gentile, F., Gericke, A., Haregeweyn, N., Hu, B., Jeanneau, A., Kaffas, K., Kiani-Harchegani, M., Villuendas, I.L., Li, C., Lombardo, L., López-Vicente, M., Lucas-Borja, M.E., Märker, M., Matthews, F., Miao, C., Mikoš, M., Modugno, S., Möller, M., Naipal, V., Nearing, M., Owusu, S., Panday, D., Patault, E., Patriche, C.V., Poggio, L., Portes, R., Quijano, L., Rahdari, M.R., Renima, M., Ricci, G.F., Rodrigo-Comino, J., Saia, S., Samani, A.N., Schillaci, C., Syrris, V., Kim, H.S., Spinola, D.N., Oliveira, P.T., Teng, H., Thapa, R., Vantas, K., Vieira, D., Yang, J.E., Yin, S., Zema, D.A., Zhao, G., Panagos, P., 2021. Soil erosion modelling: A global review and statistical analysis. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2021.146494

Borrelli, P., Ballabio, C., Yang, J.E., Robinson, D.A., Panagos, P., 2022. GloSEM: High-resolution global estimates of present and future soil displacement in croplands by water erosion. Sci Data 9. https://doi.org/10.1038/s41597-022-01489-x

Borselli, L., Cassi, P., Torri, D., 2008. Prolegomena to sediment and flow connectivity in the landscape: A GIS and field numerical assessment. Catena (Amst) 75. https://doi.org/10.1016/j.catena.2008.07.006

Cunha, E.R. da, Santos, C.A.G., Silva, R.M. da, Panachuki, E., de Oliveira, P.T.S., Oliveira, N. de S., Falcão, K. dos S., 2022. Assessment of current and future land use/cover changes in soil erosion in the Rio da Prata basin (Brazil). Science of the Total Environment 818. https://doi.org/10.1016/j.scitotenv.2021.151811

Dabral, P.P., Baithuri, N., Pandey, A., 2008. Soil erosion assessment in a hilly catchment of North Eastern India using USLE, GIS and remote sensing. Water Resources Management 22, 1783–1798. https://doi.org/10.1007/s11269-008-9253-9

Desmet, P.J.J., Govers, G., 1996. A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. J Soil Water Conserv 51, 427–433.

Ebabu, K., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Adgo, E., Fenta, A.A., Meshesha, D.T., Berihun, M.L., Sultan, D., Vanmaercke, M., Panagos, P., Borrelli, P., Langendoen, E.J., Poesen, J., 2022. Global analysis of cover management and support practice factors that control soil erosion and conservation. International Soil and Water Conservation Research. https://doi.org/10.1016/j.iswcr.2021.12.002

Elnashar, A., Zeng, H., Wu, B., Fenta, A.A., Nabil, M., Duerler, R., 2021. Soil erosion assessment in the Blue Nile Basin driven by a novel RUSLE-GEE framework. Science of the Total Environment 793. https://doi.org/10.1016/j.scitotenv.2021.148466

Flanagan, D.C., Nearing, M.A., 1995. USDA-Water Erosion Prediction Project: Hillslope profile and watershed model documentation. Nserl Rep 10, 1–123.

Food and Agriculture Organization of the United Nations., 2006. Guidelines for soil description. Food and Agriculture Organization of the United Nations.

Gomiero, T., 2016. Soil degradation, land scarcity and food security: Reviewing a complex challenge. Sustainability 8, 281.

Guo, Y., Peng, C., Zhu, Q., Wang, M., Wang, H., Peng, S., He, H., 2019. Modelling the impacts of climate and land use changes on soil water erosion: Model applications, limitations and future challenges. J Environ Manage. https://doi.org/10.1016/j.jenvman.2019.109403

Hrabalíková, M., Janeček, M., 2017. Comparison of different approaches to ls factor calculations based on a measured soil loss under simulated rainfall. Soil and Water Research 12. https://doi.org/10.17221/222/2015-SWR

Jain, M.K., Kothyari, U.C., 2000. Estimation of soil erosion and sediment yield using GIS. Hydrological Sciences Journal 45, 771–786.

Juez, C., Tena Tarruella, A., Fernández-Pato, J., Batalla, R.J., García-Navarro, P., 2018. Application of a distributed 2D overland flow model for rainfall/runoff and erosion simulation in a Mediterranean watershed. Cuadernos de investigación geográfica, 2018, vol. 44, núm. 2, p. 615-640.

Kaffas, K., Pisinaras, V., Al Sayah, M.J., Santopietro, S., Righetti, M., 2021. A USLE-based model with modified LS-factor combined with sediment delivery module for Alpine basins. Catena (Amst) 207. https://doi.org/10.1016/j.catena.2021.105655

Kashiwar, S.R., Kundu, M.C., Dongarwar, U.R., 2022. Soil erosion estimation of Bhandara region of Maharashtra, India, by integrated use of RUSLE, remote sensing, and GIS. Natural Hazards 110, 937–959. https://doi.org/10.1007/s11069-021-04974-5

Kayet, N., Pathak, K., Chakrabarty, A., Sahoo, S., 2018. Evaluation of soil loss estimation using the RUSLE model and SCS-CN method in hillslope mining areas. International Soil and Water Conservation Research 6, 31–42.

Kazamias, A.P., Sapountzis, M., 2017. Spatial and temporal assessment of potential soil erosion over Greece 315–321.

Kazamias, A.P., Sapountzis, M., Lagouvardos, K., 2017. Evaluation and intercomparison of GPM-IMERG and TRMM 3B42 daily precipitation products over Greece, in: Fifth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2017). International Society for Optics and Photonics, p. 1044413.

Knisel, W.G., 1980. CREAMS: A field scale model for chemicals, runoff, and erosion from agricultural management systems. Department of Agriculture, Science and Education Administration.

Koirala, P., Thakuri, S., Joshi, S., Chauhan, R., 2019. Estimation of Soil Erosion in Nepal using a RUSLE modeling and geospatial tool. Geosciences (Switzerland) 9. https://doi.org/10.3390/geosciences9040147

Lal, R., 2015. Restoring soil quality to mitigate soil degradation. Sustainability 7, 5875–5895.

Lele, U., Goswami, S., 2021. The Food and Agriculture Organization of the United Nations, in: Food for All. https://doi.org/10.1093/oso/9780198755173.003.0010

Li, P., Mu, X., Holden, J., Wu, Y., Irvine, B., Wang, F., Gao, P., Zhao, G., Sun, W., 2017. Comparison of soil erosion models used to study the Chinese Loess Plateau. Earth Sci Rev 170, 17–30.

Löbmann, M.T., Maring, L., Prokop, G., Brils, J., Bender, J., Bispo, A., Helming, K., 2022. Systems knowledge for sustainable soil and land management. Science of the Total Environment 822. https://doi.org/10.1016/j.scitotenv.2022.153389

Maqsoom, A., Aslam, B., Hassan, U., Kazmi, Z.A., Sodangi, M., Tufail, R.F., Farooq, D., 2020. Geospatial assessment of soil erosion intensity and sediment yield using the Revised Universal Soil Loss Equation (RUSLE) model. ISPRS Int J Geoinf 9. https://doi.org/10.3390/ijgi9060356

McCool, D.K., Foster, G.R., Weesies, G.A., 1997. Slope length and steepness factors (LS), in: Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). US Department of Agriculture Washington, DC.

Milazzo, F., Fernández, P., Peña, A., Vanwalleghem, T., 2022. The resilience of soil erosion rates under historical land use change in agroecosystems of Southern Spain. Science of the Total Environment 822. https://doi.org/10.1016/j.scitotenv.2022.153672

Morgan, R.P.C., Quinton, J.N., Smith, R.E., Govers, G., Poesen, J.W.A., Auerswald, K., Chisci, G., Torri, D., Styczen, M.E., 1998. The European Soil Erosion Model (EUROSEM): a dynamic approach for predicting sediment transport from fields and small catchments. Earth Surface Processes and Landforms: The Journal of the British Geomorphological Group 23, 527–544.

Narayana, D.V. V, Babu, R., 1983. Estimation of soil erosion in India. Journal of Irrigation and Drainage Engineering 109, 419–434.

Nekhay, O., Arriaza, M., Boerboom, L., 2009. Evaluation of soil erosion risk using Analytic Network Process and GIS: A case study from Spanish mountain olive plantations. J Environ Manage 90, 3091–3104. https://doi.org/10.1016/j.jenvman.2009.04.022

Panagos, P., Borrelli, P., Meusburger, K., 2015a. A new European slope length and steepness factor (LS-factor) for modeling soil erosion by water. Geosciences (Switzerland) 5. https://doi.org/10.3390/geosciences5020117

Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., Montanarella, L., 2015b. Estimating the soil erosion cover-management factor at the European scale. Land use policy 48. https://doi.org/10.1016/j.landusepol.2015.05.021

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Lim, K.J., Yang, J.E., Ni, J., Miao, C., Chattopadhyay, N., Sadeghi, S.H., Hazbavi, Z., Zabihi, M., Larionov, G.A., Krasnov, S.F., Gorobets, A. V., Levi, Y., Erpul, G., Birkel, C., Hoyos, N., Naipal, V., Oliveira, P.T.S., Bonilla, C.A., Meddi, M., Nel, W., Al Dashti, H., Boni, M., Diodato, N., Van Oost, K., Nearing, M., Ballabio, C., 2017. Global rainfall erosivity assessment based on high-temporal resolution rainfall records. Sci Rep 7. https://doi.org/10.1038/s41598-017-04282-8

Panagos, P., Borrelli, P., Poesen, J., 2019. Soil loss due to crop harvesting in the European Union: A first estimation of an underrated geomorphic process. Science of the Total Environment 664. https://doi.org/10.1016/j.scitotenv.2019.02.009

Panagos, P., Standardi, G., Borrelli, P., Lugato, E., Montanarella, L., Bosello, F., 2018. Cost of agricultural productivity loss due to soil erosion in the European Union: From direct cost evaluation approaches to the use of macroeconomic models. Land Degrad Dev 29, 471–484. https://doi.org/10.1002/ldr.2879

Prasannakumar, V., Vijith, H., Abinod, S., Geetha, N., 2012. Estimation of soil erosion risk within a small mountainous sub-watershed in Kerala, India, using Revised Universal Soil Loss Equation (RUSLE) and geo-information technology. Geoscience Frontiers 3, 209–215. https://doi.org/10.1016/j.gsf.2011.11.003

Raj, R., Saharia, M., Chakma, S., 2023. Mapping soil erodibility over India. Catena (Amst) 230. https://doi.org/10.1016/j.catena.2023.107271

Raj, R., Saharia, M., Chakma, S., Rafieinasab, A., 2022. Mapping rainfall erosivity over India using multiple precipitation datasets. Catena (Amst) 214. https://doi.org/10.1016/j.catena.2022.106256

Rajbanshi, J., Bhattacharya, S., 2020. Assessment of soil erosion, sediment yield and basin specific controlling factors using RUSLE-SDR and PLSR approach in Konar river basin, India. J Hydrol (Amst) 587. https://doi.org/10.1016/j.jhydrol.2020.124935

Razali, A., Ismail, S.N.S., Awang, S., Praveena, S.M., Abidin, E.Z., 2018. Land use change in highland area and its impact on river water quality: a review of case studies in Malaysia. Ecol Process 7, 1–17.

Renard et. al, 1997. Predicting soil erosion by water—a guide Equation, conservation planning with the Revised Universal Soil Loss (RUSLE). United States Department of Agriculture, Agricultural Research Service (USDA-ARS) Handbook No. 703.. ASAE Publ.

Renard, K.G., Foster, G.R., Weesies, G.A., Porter, J.P., 1991. RUSLE: revised universal soil loss equation. J Soil Water Conserv 46, 30–33.

Restrepo, J.D., Kjerfve, B., Hermelin, M., Restrepo, J.C., 2006. Factors controlling sediment yield in a major South American drainage basin: the Magdalena River, Colombia. J Hydrol (Amst) 316, 213–232.

Rose, C.W., 1999. Soil erosion models and implications for conservation of sloping tropical lands, in: Sustaining the Global Farm-Selected Papers from the 10th International Soil Conservation Organization Meeting. pp. 24–29.

Seutloali, K.E., Dube, T., Mutanga, O., 2017. Assessing and mapping the severity of soil erosion using the 30-m Landsat multispectral satellite data in the former South African homelands of Transkei. Physics and Chemistry of the Earth 100, 296–304. https://doi.org/10.1016/j.pce.2016.10.001

Sharma, N., Kaushal, A., Yousuf, A., Sood, A., Kaur, S., Sharda, R., 2022. Geospatial technology for assessment of soil erosion and prioritization of watersheds using RUSLE model for lower Sutlej sub-basin of Punjab, India. Environmental Science and Pollution Research. https://doi.org/10.1007/s11356-022-22152-3

Shinde, V., Tiwari, K.N., Singh, M., 2010. Prioritization of micro watersheds on the basis of soil erosion hazard using remote sensing and geographic information system. International Journal of Water Resources and Environmental Engineering 5, 130–136.

Singh, G., Panda, R.K., 2017. Grid-cell based assessment of soil erosion potential for identification of critical erosion prone areas using USLE, GIS and remote sensing: A case study in the Kapgari watershed, India. International Soil and Water Conservation Research 5, 202–211.

Singhvi, A.K., Krishnan, R., 2014. Past and the Present Climate of India, in: World Geomorphological Landscapes. Springer, pp. 15–23. https://doi.org/10.1007/978-94-017-8029-2_2

Swarnkar, S., Malini, A., Tripathi, S., Sinha, R., 2018. Assessment of uncertainties in soil erosion and sediment yield estimates at ungauged basins: An application to the Garra River basin, India. Hydrol Earth Syst Sci 22, 2471–2485. https://doi.org/10.5194/hess-22-2471-2018

Syvitski, J.P.M., Milliman, J.D., 2007. Geology, geography, and humans battle for dominance over the delivery of fluvial sediment to the coastal ocean. J Geol 115, 1–19.

Thomas, J., Joseph, S., Thrivikramji, K.P., 2018. Estimation of soil erosion in a rain shadow river basin in the southern Western Ghats, India using RUSLE and transport limited sediment delivery function. International Soil and Water Conservation Research 6, 111–122.

Tsegaye, L., Bharti, R., 2021. Soil erosion and sediment yield assessment using RUSLE and GIS-based approach in Anjeb watershed, Northwest Ethiopia. SN Appl Sci 3. https://doi.org/10.1007/s42452-021-04564-x

Vantas, K., Sidiropoulos, E., Evangelides, C., 2019. Rainfall Erosivity and Its Estimation: Conventional and Machine Learning Methods, in: Soil Erosion - Rainfall Erosivity and Risk Assessment. IntechOpen. https://doi.org/10.5772/intechopen.85937

Wang, X., Blake, W.H., Taylor, A., Kitch, J., Millward, G., 2021. Evaluating the effectiveness of soil conservation at the basin scale using floodplain sedimentary archives. Science of the Total Environment 792. https://doi.org/10.1016/j.scitotenv.2021.148414

Williams, J.R., 1990. The erosion-productivity impact calculator (EPIC) model: a case history. Philos Trans R Soc Lond B Biol Sci 329, 421–428.

Wischmeier, W.. H., Smith, D.D.., 1978. Predicting Rainfall Erosion Losses: A guide to Conservation Planning, in: Predicting Rainfall-Erosion Losses From Cropland East of the Rocky Mountains. United States Department of Agriculture, Agriculture Handbook No. 537, Washington , D. C.

Wischmeier, W., Smith, D., 1978. Predicting rainfall erosion losses: a guide to conservation planning, U.S. Department of Agriculture Handbook No. 537. https://doi.org/10.1029/TR039i002p00285

Wu, Q., Wang, M., 2007. A framework for risk assessment on soil erosion by water using an integrated and systematic approach. J Hydrol (Amst) 337, 11–21. https://doi.org/10.1016/j.jhydrol.2007.01.022

Xin, Z., Yu, X., Lu, X.X., 2011. Factors controlling sediment yield in China's Loess Plateau. Earth Surf Process Landf 36, 816–826.

Yamazaki, D., Ikeshima, D., Tawatari, R., Yamaguchi, T., O'Loughlin, F., Neal, J.C., Sampson, C.C., Kanae, S., Bates, P.D., 2017. A high-accuracy map of global terrain elevations. Geophys Res Lett 44, 5844–5853. https://doi.org/10.1002/2017GL072874

Zerihun, M., Mohammedyasin, M.S., Sewnet, D., Adem, A.A., Lakew, M., 2018. Assessment of soil erosion using RUSLE, GIS and remote sensing in NW Ethiopia. Geoderma Regional 12, 83–90. https://doi.org/10.1016/j.geodrs.2018.01.002

Zhang, H., Renschler, C.S., Nichols, M.H., Nearing, M.A., 2021. Long-term, process-based, continuous simulations for a small, nested rangeland watershed near Tombstone, AZ (USA): Extending model validity to include soil redistribution. Science of the Total Environment 792. https://doi.org/10.1016/j.scitotenv.2021.148403