Mapping Soil Erodibility over India

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Abstract:

Soil erosion is a major environmental problem worldwide, and almost half of India's total geographical area is susceptible to it. The Revised Universal Soil Loss Equation (RUSLE) has been widely used globally to estimate soil erosion, and Soil erodibility factor, denoted by K-factor, is an essential component of RUSLE. Although previous studies have assessed soil erodibility in India, they have been limited to small scales such as watersheds or districts. A national scale assessment of soil erodibility doesn't exist and is critical to developing a systematic understanding of soil erosion over India. In this study, we estimated soil erodibility factors over India using RUSLE Nomograph and Environmental Policy Integrated Climate (EPIC) model approaches at a high resolution of 250 m. Our results showed that the K-factor estimated using the Nomograph approach was more accurate than the observed soil erodibility factors. Additionally, we developed erodibility indices such as CR (Clay Ratio), MCR (Modified Clay Ratio), and CLOM (Critical Level of Organic Matter) to assess their sensitivity with respect to soil erodibility factors. Finally, we created a susceptibility to erosion map over India using CLOM index classification. The national average soil erodibility factor for India is estimated to be 0.028 t-ha-h/ha/MJ/mm. Histosols soil type is the least susceptible to erosion, while Xerosols soil type is most susceptible among the prevalent soil classes in India. This is the first national-scale mapping of soil erodibility over India, providing an essential asset for soil conservation and erosion management planning by experts.

Key words: Soil erodibility factor,

Clay Ratio, Modified Clay Ratio, Critical Level of Organic Matter, India, Soil erosion

Highlights:

- First national-scale mapping of soil erodibility over India.
- K-factor estimated using the widely used Nomograph and EPIC models.

- The average soil erodibility factor for India was estimated to be 0.028 t-ha-h/ha/MJ/mm.
- CLOM index highly correlated with soil erodibility in Indian condition.
- A susceptibility to soil erosion map was also created based on CLOM index over India.

1. Introduction

Soil erosion is a major trigger for land degradation and has been identified as one of the leading environmental problems, the globe is facing (Borrelli et al., 2020; Choudhury et al., 2021; Ghosh et al., 2012; Ma et al., 2003; Salesa and Cerdà, 2020; Smetanová et al., 2019). Soil erosion contributes around 15-30 billion tons of sediment which is transported annually by the major rivers of the world into oceans, accounting for approximately 46% of the total land degradation (Kulimushi et al., 2021). In India, approximately 45% of the total geographical area of the nation is susceptible to soil erosion (Bhattacharyya et al., 2015). Numerous physical and empirical models have been developed and implemented worldwide to estimate soil erosion coupled with remote sensing and geographic information system (GIS) systems covering a wide range of spatio-temporal scales (Flanagan et al., 2012; Jiang et al., 2019; Kazamias and Sapountzis, 2017; Kumar and Singh, 2021; Lobo and Bonilla, 2019; Nearing et al., 1989; Saghafian et al., 2015). Climate and soil properties also influence the erosion induced by water (Borrelli et al., 2020; Guo et al., 2019; Nearing et al., 2005; Senanayake and Pradhan, 2022). The Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1991) empirical models are widely used to estimate long-term annual soil loss. These two models (USLE and RUSLE) require less input datasets, robust, and simple to use even at large scales (Balasubramani et al., 2015). Soil erodibility (K-factor) is one of the important factors of the RUSLE model. A national scale assessment of soil erodibility will be helpful in planning and implementing watershed management activities to deal with soil erosion problem which is currently missing over India. In this study, soil erodibility factor has been modelled over India using gridded datasets at 250 m spatial resolution. This study will complement the rainfall erosivity mapping by Raj et al., (2022) in developing a systematic and comprehensive understanding of soil erosion in India.

Soil erodibility is the response of the soil profile to the erosivity induced by rainstorms and reflects the combined effect of rainfall, infiltration, and runoff on soil erosion (Bonilla and Johnson, 2012). Soil erodibility is a composite property of soil, determined by a wide range of associated parameters, but only some of these parameters are directly related to the soil types (Veihe, 2002). Ideally, soil erodibility factors would be best calculated from direct field measurements with the help of natural runoff diagrams but getting these types of records for long-term studies are too expensive and time-consuming (Dangler and El-Swaify, 1976; Efthimiou, 2020; Torri et al., 1997; Young and Mutchler, 1977). So, various attempts had been made to correlate soil properties with the measured soil erodibility factors (Cohen et al., 2005; Wang et al., 2022). The widely adopted relationship to estimate K-factor is the soil erodibility nomograph approach (Wischmeier and Smith, 1978) which uses more easily obtainable datasets such as soil texture, structure, permeability and SOM (soil organic matter) (Efthimiou, 2020). Soil erodibility factors were also estimated by Torri et al., (1997) using clay content of the soil, soil organic matter (SOM), and the Naperian logarithm of the geometric mean particle diameter. Romkens et al., (1986) developed a relation depending upon four regression coefficients and particle size distribution to estimate soil erodibility factors. An equation was also developed by Mulengera and Payton (1999) to calculate K-factor for tropical regions using SOM, soil permeability and soil texture data. Although these models were estimating soil erodibility values with various degrees of excellence, but could not provide the distribution of soil erosion spatially due to the complex environment of the model, and hence not suitable for modelling over larger areas (Lu et al., 2004).

Predicting soil erodibility factor spatially, and its geospatial upscaling is very sensitive to the methods and models used in the study. The properties of soil which directly control K-factors are shear strength, porosity, organic matter, permeability, bulk density, shape and size of aggregates, particle size distribution, and chemical composition of soil (Chen and Zhou, 2013).

The performance of the models depends on the physical, biological, mineralogical, and chemical processes within the models. Being highly dynamic in nature, K-factor rationalizes the effect of various intrinsic soil properties on erosion (Wang et al., 2001). Environmental Policy Integrated Climate (EPIC) Model (Williams et al., 1983) had been used by Godoi et al., (2021), to estimate soil erodibility factors across Brazil.

As discussed, empirical equations and models are widely used globally to assess the sensitivity of model outputs to field-based erodibility factor values. However, due to the nature of data inclusion and availability for the study location, it is imperative to look beyond a single equation or model globally to capture impact of model variability on soil erodibility estimates. The global research community now focuses on building composite models that might replicate the field-based soil erodibility variables with greater accuracy. RUSLE's Nomograph with other models like EPIC and erodibility indices had been estimated at the watershed or regional scale across the world. In this research, the applicability of these models and indices have been thoroughly assessed over the study region.

In India, pedological datasets are either unavailable at a national scale or are dispersed between various research institutes and public agencies. Such problems compel researchers and scientists to adopt empirical equations to estimate soil erodibility factor (Adhikary et al., 2014; Mhaske et al., 2021; Olaniya et al., 2020; Paparrizos et al., 2015; Rozos et al., 2013). Very few studies have been performed over the Indian region to calculate K-factors using field observations (Adhikary et al., 2014; Bera, 2017; Olaniya et al., 2020). Adhikary et al., (2014) estimated K-factors for Bundelkhand regions in Central India using four different empirical models.

Olaniya et al., (2020) estimated soil erodibility and erodibility indices over Ri-Bhoi district of Meghalaya. In absence of actual K-factor values, erodibility indices such as Clay Ratio (CR) (Bennett, 1926), Modified Clay Ratio (MCR) (Kumar et al., 1995), and Critical Level of Soil

Organic Matter (CLOM) (Pieri, 2012) indices have been used to estimate soil erodibility. Soil erodibility factors for Europe, mapped by Panagos et al., (2014) has been incorporated by many scientists and researchers as input forcing data for their soil erosion models in Europe. Estimation of soil erodibility over India thus remains a significant milestone required to develop policy and tools useful for developing soil conservation and erosion mitigation plans. In this study, we estimated soil erodibility factors over national scale using RUSLE Nomograph (K_{NOMO}) and EPIC (K_{EPIC}) models. A detailed statistical evaluation of soil erodibility map was also performed to visualize its distribution over the national region based on soil types, texture, and percentage-range of erodibility values. Erodibility indices like CR, MCR, and CLOM indices were estimated over India and its sensitivity with soil erodibility was also checked. The soil erodibility index which was correlating K-factor with better accuracy was plotted in scatter manner as well. CLOM index generally refers to the critical availability of the organic carbon in soil, higher CLOM ratio suggests less susceptibility to soil erosion. A susceptibility to soil erosion map was finally developed over India using CLOM index classification. This study will provide a comprehensive understanding of the soil erodibility factor and its indices over India and provide an additional K-factor dataset to perform soil loss estimations over the national scale.

2. Materials and Methodology

2.1 Study Area

This study covers the political boundary of India, with an area equal to 36,57,948 km^2 between 68°7' - 97°25' and 8°4' - 37°6' longitude and latitude respectively. As the seventh largest nation in the world by geographical area, an immense diversity distribution of soil types and properties associated with itis observed throughout the country. A total of 18 classes of soils are present according to the FAO-UNESCO (Food and Agriculture Organization – United Nations Educational, Scientific and Cultural Organization) Soil Map of the World, which has been shown in Figure 1.

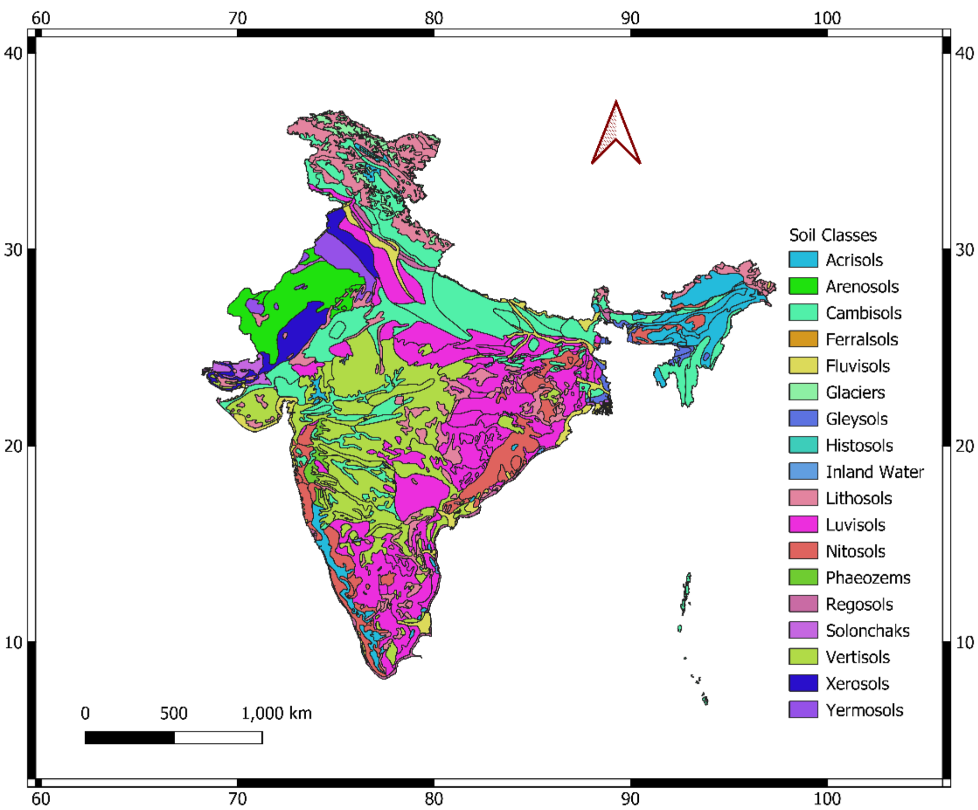

Figure 1. Soil classes of India (Source: FAO-UNESCO Soil Map of the World)

Lithosols soil covers the maximum are (24.14%) while Ferralsols soil in minimum area (0.02%) of the total land of the country. About 70% of the total land area of the nation is covered by only four classes of soils (Lithosols (24.14%), Cambisols (16.93%), Luvisols (16.12%) and Vertisols (13.12%)). Rest of the 14 soil classes (Acrisols, Arenosols, Ferralsols, Fluvisols, Glaciers, Gleysols, Histosols, Nitosols, Phaeozems, Regosols, Solonchaks, Xerosols, Yermosols, and Inland water) acquire only 30% of the total soil surface of the study area. Considering the texture classes, as per the record of NBSS&LUP (National Bureau of Soil Survey and Land Use Planning) India, about 45.12% of the total spread area of the nation is loamy in nature, while 33.14% clayey and 11.17% sandy. About 7.56% of the total area consists of Glaciers and Rock outcrops, 1.62% water bodies, 0.67% Rock mountains, and about 0.64% area covers the Rann of Kachchh.

2.2 Data acquisition and preparation

For estimating soil erodibility factor (K-factor) and the erodibility indices {Clay Ratio (CR), Modified Clay Ratio (MCR), and Critical Level Organic Matter (CLOM)} over India, gridded datasets associated with soil particle properties have been utilized. The datasets required were percentage of sand, silt, clay, soil organic carbon (SOC), soil organic matter, soil texture class, soil structure code (SSC), and soil permeability code (SPC). Percentage of sand, silt, clay, and SOC were downloaded from SoilGrids of ISRIC (International Soil Reference and Information Centre) (https://soilgrids.org/) (Hengl et al., 2017). Texture classes were prepared using percentages of soil particles size data utilizing Soil Texture Calculator Triangle from NRCS (Natural Resources Conservation Service) Soils – USDA (United States Department of Agriculture). SSC and SPC were mapped using the prepared soil texture and soil groups information at national scale.

2.2.1 Soil particles properties

SoilGrids is a platform where soil profile datasets are compiled using machine learning methods to produce digital soil map over the globe. Global soil profile datasets are available at WoSIS (World Soil Information Service). More than 230000 soil profiles, and a series of environmental covariates are used to fit the SoilGrids prediction models. Various datasets associated with soil parameters are available on SoilGrids website. In this research, properties of soil particles such as content of silt, sand, clay, and soil organic carbon (SOC) had been used. These datasets were downloaded using Google Earth Engine (GEE) at 250 m resolution for entire India. The units of contents of sand, clay and silt are same i.e., weight percentage (g/g), but the unit of SOC is in g/kg. Soil organic matter (SOM) were also used in this study. Since the exact available organic matter data was unavailable, a conversion factor equal to 2 was adopted in this research to convert SOC to SOM (Pribyl, 2010). Data of very fine fraction of sand was also not available at national scale, so a factor of 0.02 (20%) to the percentage content of sand particles was adopted based on Panagos et al. (2014).

2.2.2 Soil Texture Class

Natural Resources Conservation Service Soils (NRCS) of United States Department of Agriculture (USDA) has suggested the soil texture calculator triangle to calculate texture classes. Ranges of texture classes have been retrieved using the triangle which is shown in Table 1. In this classification system, the contents of sand, silt and clay have been considered to assign a texture class. Using this concept, texture classes (Sand, silt, clay, sandy loam, loamy sand, loam, silt loam, sandy clay loam, clay loam, sandy clay, silty clay loam, clay, and silty clay) were mapped throughout the nation.

Table 1. Ranges of contents of sand, silt, and clay for texture classification (NRCS-USDA)

Texture Class	Sand %	Silt %	Clay %
Sand	85-100	0-15	0-10
Sandy loam	43-85	0-50	0-20
Loamy sand	70-90	0-30	0-15
Loam	23-52	28-50	7- 27
Silt loam	0-50	50-88	0-27
Sandy Clay Loam	45-80	0-28	20-35
Clay Loam	20-45	15-53	27-40
Sandy Clay	45-60	0-20	35-55
Silty Clay loam	0-20	40-73	27-40
Clay	0-45	0-40	40-100

Silty Clay	0-20	40-60	40-60
Silt	0-20	80-100	0-12

2.2.3 Soil Structure and Permeability Class

Soil texture classes prepared using NRCS-USDA classification were further processed to assign texture and permeability classes over India. Sand texture class is generally blocky, platy, or massive in nature. Medium or coarse granular soil particles cover sandy loam, loamy sand, loam, silt loam, sandy clay loam, clay loam, sandy clay, and silty clay loam; while fine granular soils cover clay, silty clay and silt (Morgan, 2001). Structure and permeability classes were classified and shown in Table 2.

Table 2. Soil structure and permeability classes based on texture class (Efthimiou, 2020; Morgan, 2001)

Texture Class	Soil	Structure	Permeability
Sand	Blocky, Platy or Massive	4	1
Sandy loam	Medium or coarse granular	3	2
Loamy sand	Medium or coarse granular	3	2
Loam	Medium or coarse granular	3	3
Silt loam	Medium or coarse granular	3	3
Sandy Clay Loam	Medium or coarse granular	3	4
Clay Loam	Medium or coarse granular	3	4
Sandy Clay	Medium or coarse granular	3	5
Silty Clay loam	Medium or coarse granular	3	5
Clay	Fine granular	2	6
Silty Clay	Fine granular	2	6
Silt	Fine granular	2	6

2.3 Methodology

Soil erodibility factors over India were mapped using two approaches – empirical methods and indices. In the first method, soil erodibility factors were estimated using two widely used models i.e., RUSLE Nomograph (K_{NOMO}) and EPIC Model (K_{EPIC}); while in the second method, soil erodibility indices such as clay ratio (CR), modified clay ratio (MCR), and critical level of organic matter (CLOM) were calculated. The complete methodology followed for the soil erodibility mapping is given in Figure 2. Soil texture classes were prepared using NRCS-USDA soil texture triangle (NRCS, 2016). Soil structure and permeability codes were also mapped over the study area the prepared texture class with the help of the concept suggested by Morgan (2001).

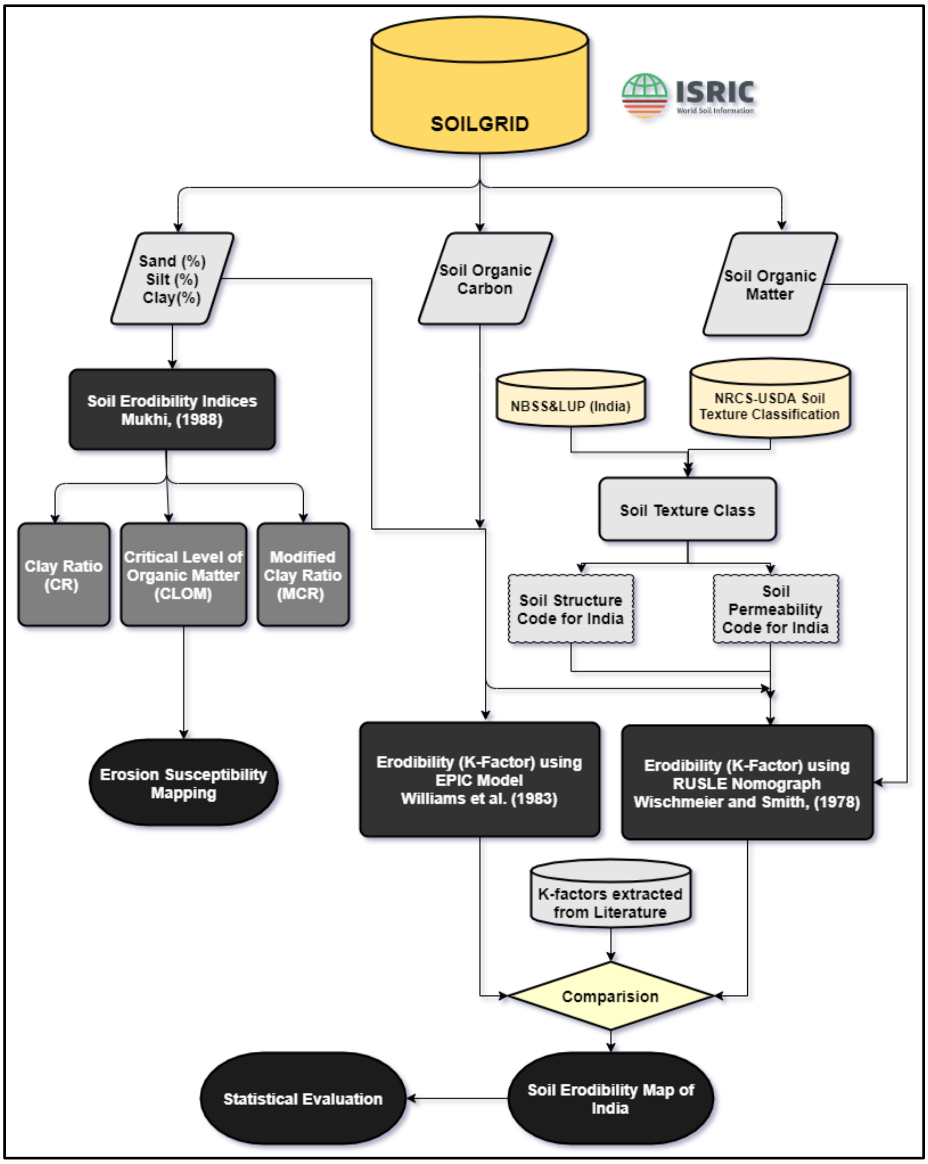

Figure 2. Workflow methodology for soil erodibility mapping over India

Further, a comparative analysis was also performed among the soil erodibility factors (K_{NOMO} and K_{EPIC}) and erodibility indices (CR, MCR and CLOM) to check the correlation. K-factor maps were compared with past studies in India. A detailed statical analysis of the soil erodibility map was also conducted to illustrate its distribution over the national region based on soil types, texture, and percentage-range erodibility values. A susceptibility map due to soil erosion was also prepared using the CLOM index values with the help of the concept suggested by Pieri, (2012). Arcmap 10.5, Google Earth Engine, Q-GIS 3.16, and Python libraries in Jupyter Notebook had been used to process and visualize the data.

2.3.1 Soil Erodibility Factor (K-factor)

Soil erodibility is a function of the content of sand, silt, clay, percentage of soil organic matter (SOM), permeability, and structure code (Renard et al., 1997; Wischmeier and Smith, 1978); and can be expressed as Equation 1.

$$K_{NOMO} = 0.1317\{\left(2.1\, M^{1.14} *\ 10^{-4} *\ (12 - SOM) + 3.25\,(s-2) + 2.5\,(p-3)\right) \div 100\}$$

(Eq. 1)

Where: K_{NOMO} = Soil erodibility factor using Nomograph approach in t-ha-h/ha/MJ/mm

M = {(% of silt + % of very fine sand) * (100 - % of clay)} = Particle size parameter

SOM = Percentage of soil organic matter

s = Soil structure code

p = Soil permeability code

The multiplication factor 0.1317, coverts the unit of K-factor into SI unit i.e., t-ha-h/ha/MJ/mm. Percentage of very fine sand (vfs) was calculated as 20% of content of sand. Nomograph equation was defined for those types of soil profile where silt content is not more than 70%.

Williams et al., (1983) developed a model named EPIC (Environmental Policy Integrated Climate) to determine the relationship between soil productivity and soil erosion. The components of the model also include hydrology, tillage science, plant growth, nutrient dynamics, soil temperature, and economics. There were various physical components included in this model to describe the soil productivity and erosion phenomena. Soil erodibility factor using EPIC model approach (K_{EPIC}) is dependent on percentage of soil particle size (sand, silt, and clay) and soil organic carbon (SOC) only, expressed as shown in Equation 2.

$$K_{EPIC} = 0.1317\left(0.2 + 0.3 *\ e^{\left(-0.0256 * SAND\left(1-\left(\frac{SILT}{100}\right)\right)\right)}\right) * \left(\frac{SILT}{CLAY+SILT}\right)^{0.3} * \left(1 - \left(0.25 * \frac{SOC}{SOC + e^{(3.72-2.95*SOC)}}\right)\right) * \left(1 - \left(0.7 * \frac{SN}{SN + e^{(-5.51+22.9*SN)}}\right)\right) \qquad \text{(Eq. 2)}$$

Where: K_{EPIC} = Soil erodibility factor in t-ha-h/MJ/ha/mm

CLAY = % of clay content

SILT = % of silt content

SAND = % of sand content

SOC = % of soil organic carbon

SN = {1 – (SAND/100)}

The multiplication factor 0.1317, coverts the unit of K-factor into SI unit i.e., t-ha-h/ha/MJ/mm. Input data for K_{EPIC} was derived from SoilGrids up to depth of 30 cm from top.

2.3.2 Erodibility Indices

In the second method, to estimate soil erodibility factor erodibility indices like CR, MCR and CLOM were calculated over India. Clay ratio (CR) is the property of soil by which binds the soil particles tightly. Higher the number of clay particles, higher the clay ratio, and harder it is to detach the soil particles by external forces (Bouyoucos, 1935). Clay ratio is inversely proportional to K-factor. Clay ratio was further modified by introducing content of soil organic matter (SOM) into it, and termed as modified clay ratio (MCR) (Mukhi, 1988; Tarafdar and Ray, 2005). The clay ratio and modified clay ratio are shown in Equation 3 and Equation 4 simultaneously.

$$CR = \{\frac{(\%SAND + \%SILT)}{\%CLAY}\} \quad \text{(Eq. 3)}$$

$$MCR = \{\frac{(\%SAND + \%SILT)}{(\%CLAY + \%SOM)}\} \quad \text{(Eq. 4)}$$

Where: % (SAND, SILT, CLAY, SOM) = % of sand, silt, clay, and soil organic carbon.

Further, CLOM is also an index for soil erodibility and indicates the susceptibility caused due to soil erosion (Pieri, 2012). It refers to the relative content of the soil organic matter (SOM) available in the soil samples and expressed as shown in Equation 5.

$$CLOM = \left(\frac{SOM}{CLAY+SILT}\right) \quad \text{(Eq.5)}$$

Where: CLOM = Critical level of Organic matter

SOM, SILT and CLAY = Percentages of soil organic matter, silt, and clay content.

Lower values of CLOM refer to the higher susceptibility due to erosion. A detailed description of CLOM values with respect to susceptibility due to soil erosion is shown in Table 3. A susceptibility map due to soil erosion had been mapped over India using the classification concept given in Table 3 which is based on the percentage occurrence of the critical level of organic matter. Availability of organic matters in the soil provide strength against soil erosion it implies that lower the CLOM values, the greater the vulnerability to soil erosion. Best correlated erodibility index was also plotted against K-factor to visualize its variation corresponding to soil texture classes defined by NBSS & LUP, India.

Table 3. Classification of CLOM values for susceptibility due to erosion (Pieri, 2012)

Sr No	CLOM (%)	Susceptibility to Soil Erosion
1	(<5)	High
2	(5-7)	Moderate
3	(7-9)	Low
4	(>9)	Stable

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3. Results and Discussions

3.1 Erodibility Factors

Soil particle parameters (percentage of sand, silt, clay, structure code, permeability code, SOC, SOM, and vfs) had been used to estimate K-factors using Nomograph and EPIC model approaches. Soil erodibility factor maps (K_{NOMO} and K_{EPIC}) have been shown in Figures 3 (a) and (b) respectively. The national average soil erodibility value for India was calculated as 0.028 and 0.034 t-ha-h/ha/MJ/mm using Nomograph and EPIC model approaches respectively. A detailed statistics of K-factors has been shown in Table 4.

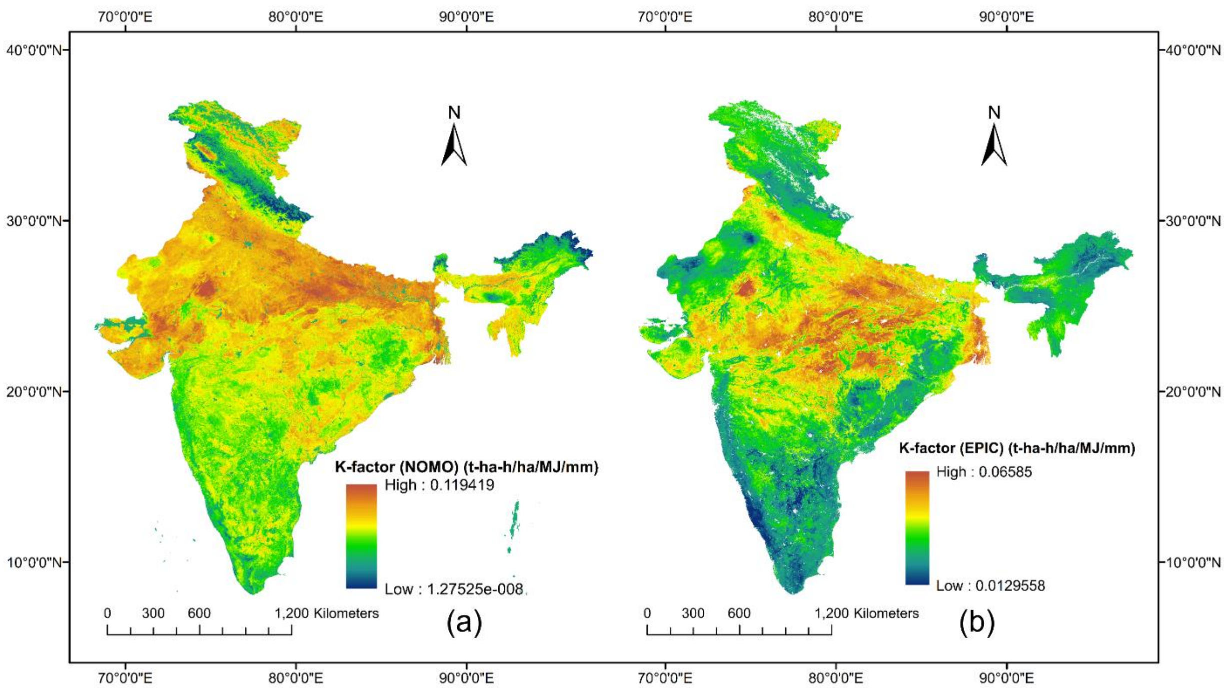

Figure 3. (a) and (b) Soil erodibility factor maps (K_{NOMO} and K_{NOMO}) over India using RUSLE Nomograph and EPIC models respectively

Table 4. Statistical summary of erodibility factors and indices K-factor

Parameters	Minimum	Maximum	Average	Standard Deviation
K-EPIC	0.013	0.065	0.034	0.004
K-NOMO	1.27 * 10^(-8)	0.11	0.028	0.007
CR	0.77	10.776	2.32	0.85

MCR	0.000	8.05	2.07	0.67
CLOM	0.000	24.1	2.96	2.222

The Nomograph approach for calculating K-factor allows the SOM less than or equal to 12 as mentioned in Equation 1 with {(12 – SOM)} term. In this study, SOM values were estimated in the range of 0 to 22.52%. The term associated with permeability code (p) in Equation 1 also effected negatively by the permeability codes 1 and 2 which generally refer to the soil types with blocky, platy, or massive, medium, or coarse granular soil particles. It was observed that these factors were responsible to reflect negative values of K-factor using Nomograph method. These negative values were only 0.22% of the total pixels in the study region. It was observed that the negative values were ranged from 0 to -0.017 and occurred in the regions having soil types with blocky, platy, or massive, medium, or coarse granular soil particles which have higher resistivity to soil erosion. To rectify these negative values, the modulus of K-factor was incorporated. Lower values of K-factor reflect higher resistivity against soil erosion.

Higher values of erodibility refer to the high susceptibility due to soil erosion in those regions and vice versa (Kumar and Kushwaha, 2013). It was also observed that K-factors estimated using EPIC model had been overestimated the soil erodibility values than that of Nomograph model. A difference map had been created between K_{EPIC} and K_{NOMO} maps, which has been shown in Figure 4. The difference K-factor values ranges from -0.025 to 0.035 t-ha-h/ha/MJ/mm. This map was created by subtracting K_{NOMO} values from K_{EPIC} values, and it was observed that about 85% values were overestimated using EPIC model. This could be due to the parameters taken to estimate soil erodibility by both the models. EPIC model does not count the structure and permeability codes while these two parameters are associated with the Nomograph model and creates adequate impact on the soil erodibility estimated using this model. Taking into account the structural and permeability factors of soil, it offers additional information about the qualities of soil particles that is crucial for preventing soil erosion by influencing soil erodibility values.

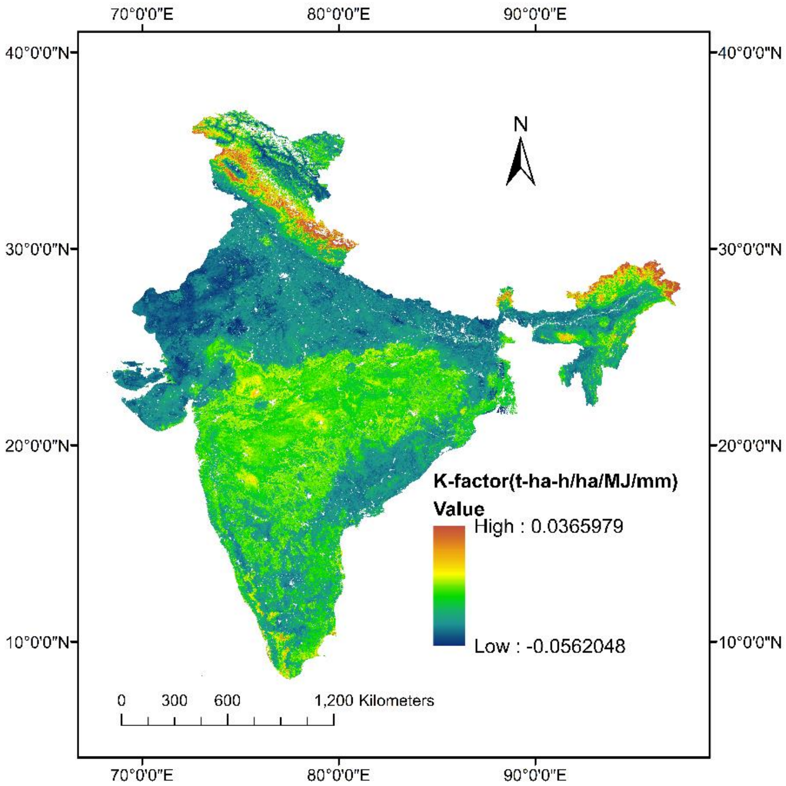

Figure 4. Difference map of K-factor estimated using EPIC model compared with Nomograph model

3.2 Erodibility Indices

Clay ratio (CR) and Modified Clay Ratio (MCR) were calculated using percentage content of sand, silt, clay, and SOM present in the soil samples, which have been shown in Figures 5(a) and (b). Average CR and MCR for India was calculated as 2.32 and 2.07, while maximum as 22.81 and 17.42 respectively. The differences in the spatial variation of these two indices could be visualize in Figure 5(a) and (b) where higher values (>5) were spotted in the northern upper side of the study region (Jammu and Kashmir, Himanchal Pradesh) and some portions of Arunachal Pradesh, Punjab, and Sikkim states of India. These differences are due to the consideration of organic matter availability in modified clay ratio which reduces the value of MCR in comparison to CR.

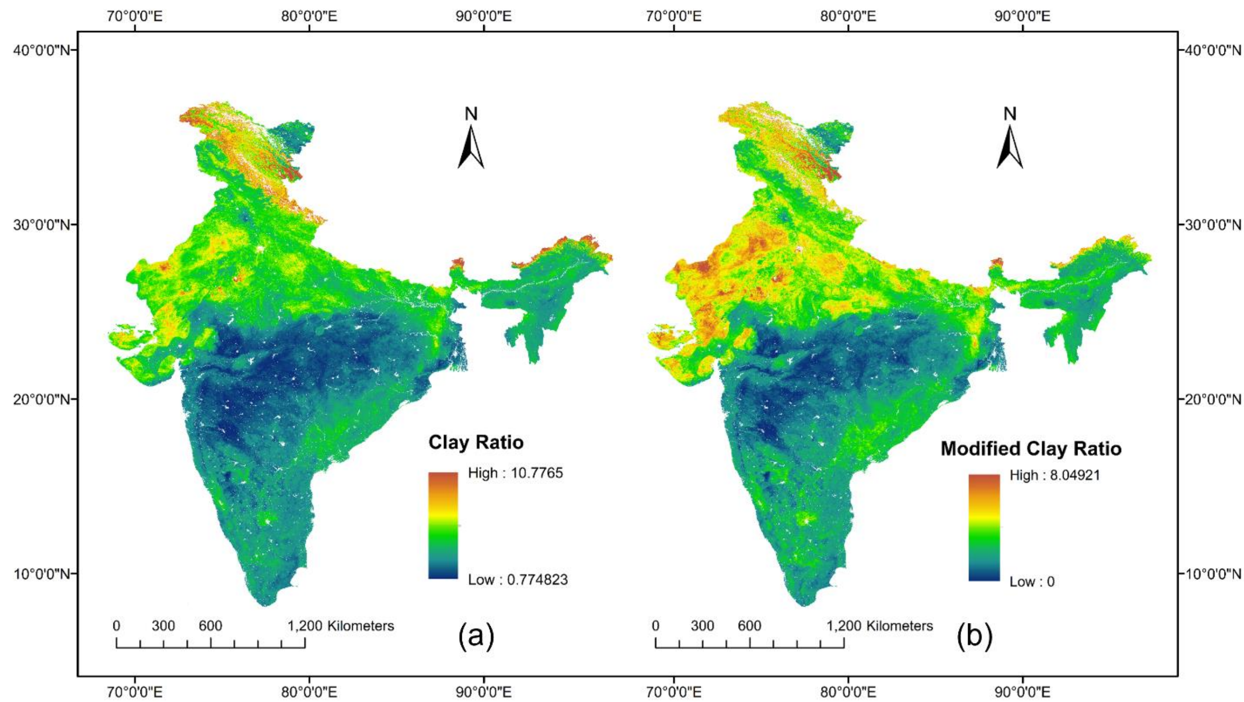

Figure 5. (a) and (b) Clay Ratio (CR) and Modified Clay Ratio (MCR) Maps over India

Higher clay ratio suggests a greater potential to avoid soil erosion which means lower susceptibility to soil erosion. Higher CR values were spotted in the border areas of Arunachal Pradesh, Sikkim, Uttarakhand, Himanchal Pradesh, and a few regions of Rajsthan and Jammu and Kashmir; while lower values were spotted in the regions of Central India (Figure 5 (a)). Apart from the regions covered by higher CR values, MCR also covered major portions of Rajsthan, Gujarat, and some regions of Uttar Pradesh and Haryana having higher values which referred to the low susceptibility due to soil erosion in these regions (Figure 5 (b)).

Critical level of organic matter (CLOM) ratio was calculated using the soil particles parameter datasets over India which has been shown in Figure. 6. As indicated by the name itself, this index refers to the availability of the relative content of SOM which suggests that higher

CLOM values are less susceptible to soil erosion. The CLOM map was further classified in susceptibility classes due to soil erosion (Pieri, 2012) according to Table 3, which has been shown in Figure 6. Only border areas of Arunachal Pradesh, Sikkim, Uttarakhand, Himanchal Pradesh, and some regions of Jammu and Kashmir were identified as stable regions due to soil erosion considering the higher CLOM values. Major portion of the country (>80%) areas were spotted as high susceptible regions due to soil erosion having lower CLOM values.

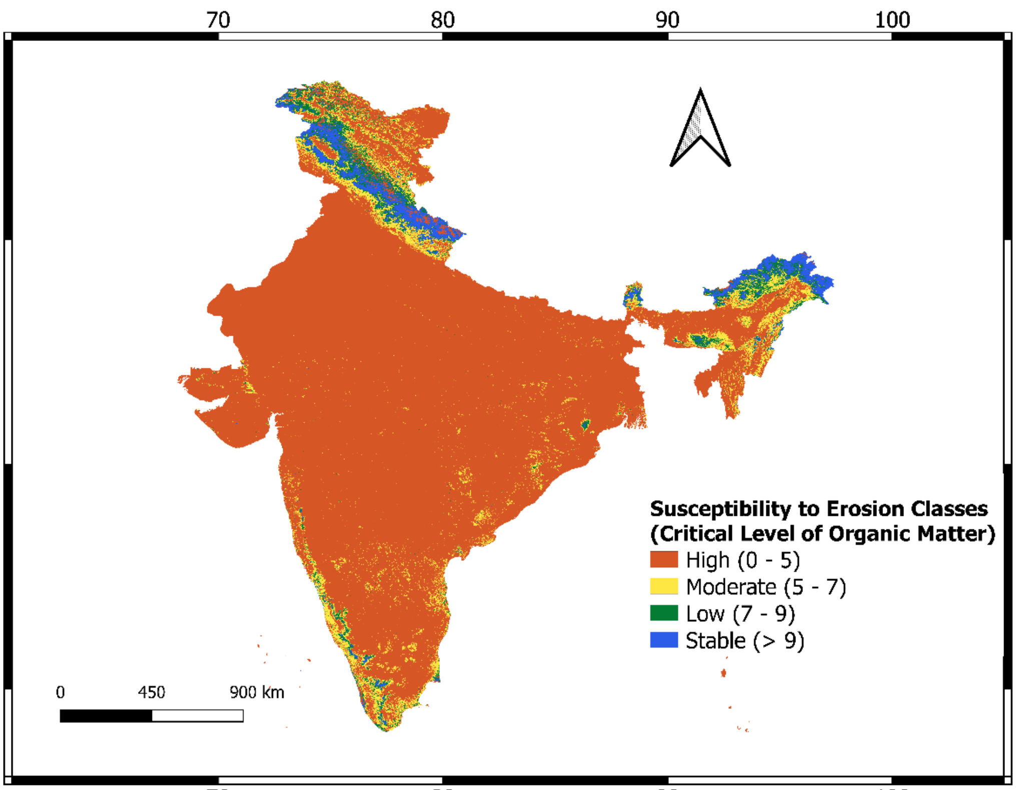

Figure 6. Susceptibility to soil erosion classes based on Critical Level of Organic Matter (CLOM) values

3.3 Relationship between K-factors and erodibility indices

Erodibility indices (CR, MCR and CLOM) had been used as an alternate approach to estimate soil erodibility earlier. These indices were further compared with the K-factors estimated using both models (K_{NOMO} and K_{EPIC}) in this study. Pearson's correlation coefficients were calculated among erodibility indices and K-factors which is shown in Table 5. Erodibility factors computed using both the methods was giving a correlation coefficient of 0.64 despite showing overestimation in calculating K-factor by EPIC method. It was observed that only CR with MCR, and CLOM index with K_{NOMO} was correlating with better accuracy having Pearson's correlation equals to 0.95 and -0.73 respectively. Negative correlation shows that if the value of CLOM index increases, the values of K_{NOMO} decreases; and vice versa. Clay ratio was worst correlated with K-factors estimated using both methods having correlation coefficients 0.07 and -0.17 because of the data requirements to calculate these parameters. Clay ratio only incorporates sand, silt, and clay percentages while Nomograph and EPIC models use soil particle parameters and content of SOC as additional input data. Best correlated erodibility (CLOM) index was further plotted against K-factor to visualize its variation corresponding to soil texture classes defined by NBSS & LUP, India which has been shown in Figure 7.

Table 5. Correlation coefficients among K-factors and erodibility indices

	CR	MCR	CLOM	K_{NOMO}	K_{EPIC}
CR	1	0.95	0.43	0.07	-0.17
MCR	0.95	1	0.15	0.33	-0.08
CLOM	0.43	0.17	1	-0.73	-0.52
K_{NOMO}	0.07	0.33	-0.73	1	0.64
K_{EPIC}	-0.17	-0.07	-0.52	0.64	1

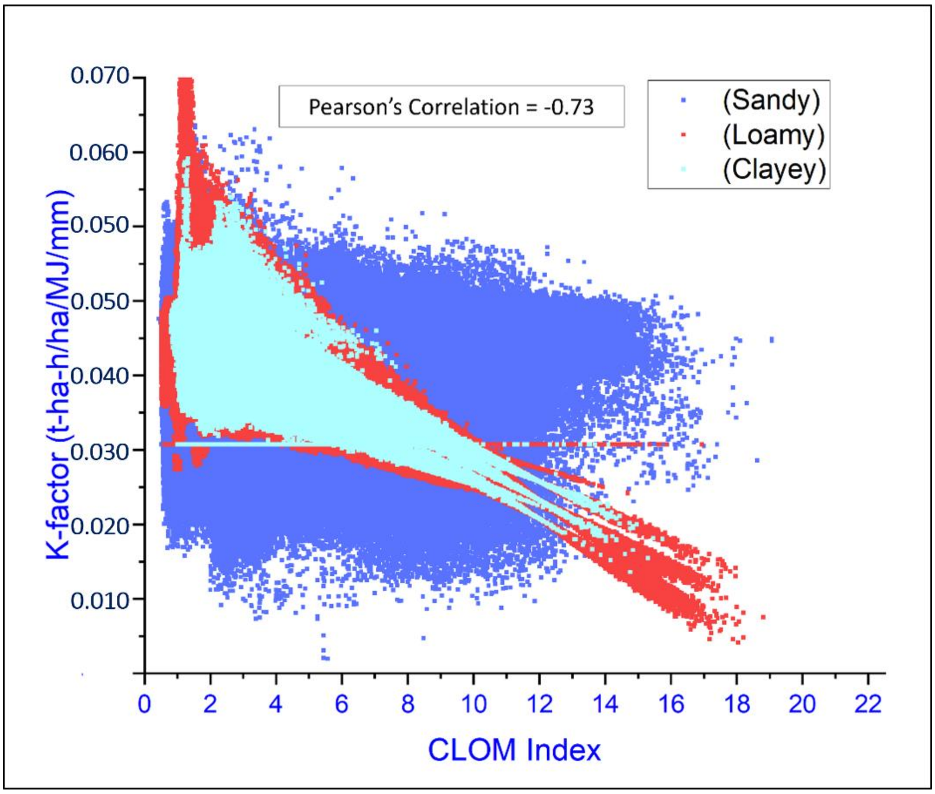

Figure 7. Scatter plot between K-factors (t-ha-h/ha/MJ/mm) and Critical Level of Organic Matter (CLOM) index highlighting for major soil texture classes (Loamy, Clayey, and Sandy).

3.4 Distribution of soil erodibility (K-factor)

The average soil erodibility factors (K_{NOMO} and K_{EPIC}) for India are estimated as 0.028 and 0.034 respectively. The soil types and texture classes are not uniform though out the nation leading to the spatial variability of K-factors in India. Both the K_{NOMO} and K_{EPIC} factors were compared with the few existing studies that have been conducted in India. Bera, (2017) had estimated soil erosion for Gumti river basin of Tripura, India, where he had also estimated soil erodibility values. Olaniya et al., (2020) also estimated K-factors for Ri-Bhoi district of Meghalaya, India. These two K-factors were collected by the authors, and a statical comparison (Minimum, maximum, and average) with the estimated K-factors has been shown in Table 6. The K-factor values mentioned in the literature were converted into the SI unit (t-ha-h/ha/MJ/mm) to compare with calculated K-factors using both the methods.

Table 6. Comparison of estimated K-factor values with the extracted K-factors from literature

	Gumti River Basin (Tripura, India)			Ri-Bhoi District (Meghalaya, India)		
	K_{NOMO}	K_{EPIC}	K-Literature	K_{NOMO}	K_{EPIC}	K-Literature
Minimum	0.014	0.029	0.012	0.014	0.026	0.011
Maximum	0.043	0.043	0.047	0.041	0.040	0.055
Average	0.030	0.034	0.035	0.026	0.029	0.029

By analyzing the values of K-factors from Table 6, it was observed that K_{NOMO} shows relatively better relationship with the K-factors reported in the literature based on the minimum, maximum, and average values. The erodibility factor was estimated in the range of (0 to 0.054 t-ha-h/ha/MJ/mm) (Godoi et al., 2021) for Brazil, (0.013 to 0.044 t-ha-h/ha/MJ/mm) (Efthimiou, 2020) for Greece, (0.02 to 0.05 t-ha-h/ha/MJ/mm) (Bonilla and Johnson, 2012) for Central Chile, (0.02 to 0.07 t-ha-h/ha/MJ/mm) (Yang et al., 2018) for New South Wales, Australia, and (0.026 to 0.076 t-ha-h/ha/MJ/mm) (Panagos et al., 2014) for European countries. Adhikary et al., (2014) had also mapped K-factors in Bundelkhand region of Central India which covers thirteen districts of Madhya Pradesh and Uttar Pradesh using four models. The average K-factors extracted from the research paper published by Adhikary et al., (2014) was about 0.032 t-ha-h/ha/MJ/mm, which was matching with the average K-factor value (0.034 t-ha-h/ha/MJ/mm) estimated by Nomograph approach (K_{NOMO}). This, for further mapping of the distribution of K-factors throughout the national region, we adopted the K_{NOMO} values as the standard. Total number of pixels available in the K-factor map of India, were grouped in five ranges which has been shown in Figure 8. About 96.6% of the pixels of K-factors were spotted in the range of (0.013-0.046) t-ha-h/ha/MJ/mm, while only 2.9% values were less than 0.013 t-ha-h/ha/MJ/mm, and 0.4% values of K-factor were recorded more than 0.0467 (t-ha-h/ha/MJ/mm). About 55.8% of the K-factor values were greater than the national average K-factor (0.028 t-ha-h/ha/MJ/mm).

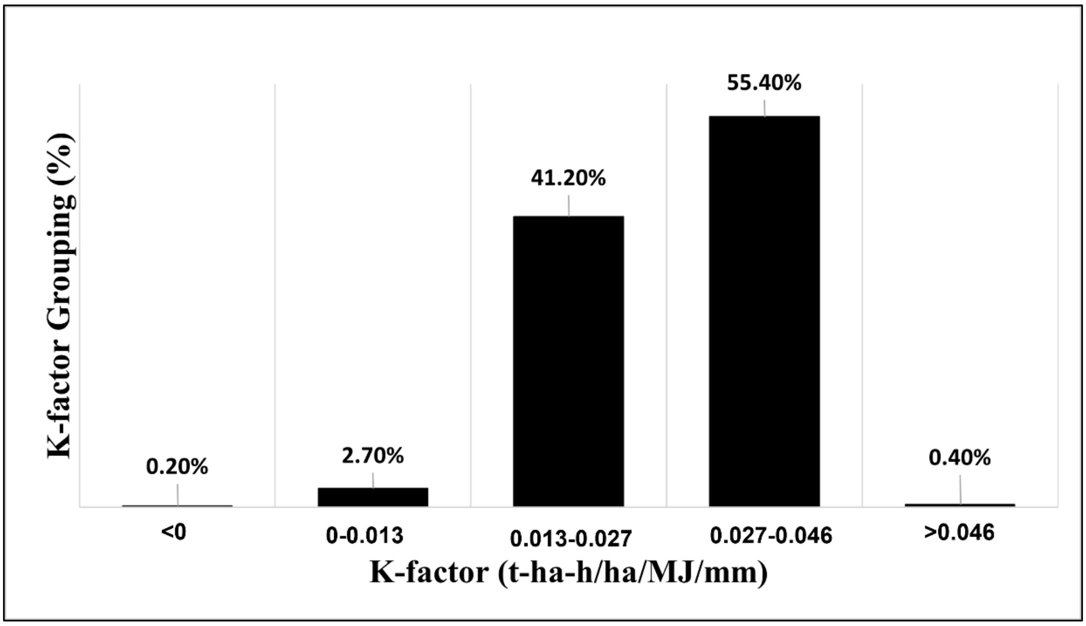

Figure 8. Distribution of the range of K-factors (t-ha-h/ha/MJ/mm) grouped in percentages in the form of bar-chart

To make the study usable at the policy level, the K_{NOMO} map was used to extract average K-factor values for the soil classes defined by FAO-UNESCO. Considering the soil classes across the country, Histosols soil type was observed as least susceptible to soil erosion having lowest average K-factor (0.011 t-ha-h/ha/MJ/mm) while Xerosols soil type was most susceptible to soil erosion having highest average K-factor (0.034 t-ha-h/ha/MJ/mm) corresponding to the particular soil classes in Indian condition. These soil classes can be refereed to Figure 1 for better visualization of the distribution of the soil classes. About 71% of the national spread area was spotted as average K-factor values greater than national average K-factor (0.028 t-ha-h/ha/MJ/mm) which covered eight (Vertisols, Luvisols, Gleysols, Fluvisols, Cambisols, Arenosols, Yermosols, and Xerosols) out of the eighteen soil classes.

4. Conclusions and Future Work

This study is an attempt to map soil erodibility and its distribution throughout the nation and check the applicability of erodibility indices to estimate soil erodibility factor in the Indian region. High resolution (250 m) input datasets for soil erodibility estimation from SoilGrids had been downloaded and processed to get K-factor and erodibility indices over India. The conclusions of this study are as follows:

- Using two widely adopted soil erodibility models (RUSLE Nomograph, and EPIC Model), it is observed that K-factors estimated using Nomograph model (K_{NOMO}) shows better agreement with the past studies.
- National average soil erodibility factor for India were estimated as 0.028 and 0.034 t-ha-h/ha/MJ/mm using Nomograph and EPIC models respectively.
- About 96.6% values of K-factors were spotted in the range of (0.013-0.046) t-ha-h/ha/MJ/mm, while only 0.4% values of K-factor were recorded more than 0.046 (t-ha-h/ha/MJ/mm). About 55.8% of the K-factor values were greater than the national average K-factor (0.028 t-ha-h/ha/MJ/mm).
- Histosols soil type was observed as least susceptible to soil erosion having lowest average K-factor (0.011 t-ha-h/ha/MJ/mm) while Xerosols soil type was most susceptible to soil erosion having highest average K-factor (0.034 t-ha-h/ha/MJ/mm) corresponding to the soil classes in Indian condition.
- Soil erodibility indices (CR, MCR, and CLOM index) had been also compared with the K-factors (K_{NOMO} and K_{EPIC}) to check the relationships of these indices with K-factor. It was observed that only CLOM index was showing better correlation (Pearson’s correlation = -0.73) with K_{NOMO} in Indian condition.
- A susceptibility to soil erosion map was also created based on CLOM index over India and it was observed that only the border regions of Arunachal Pradesh, Sikkim, Uttarakhand, Himachal Pradesh, and some regions of Jammu and Kashmir were spotted as stable zones due to soil erosion.

This is the first national-scale mapping of soil erodibility factor over India which will be an important asset for soil and erosion management planning by experts. This study will complement the national mapping of rainfall erosivity (Raj et al., 2022) in an effort to develop a systematic and comprehensive understanding of soil erosion over India. Since extensive local ground measurements were not available for this study, global gridded datasets were utilized instead. However, these datasets have their own limitations, depending on the statistical approaches used to interpolate point spatial values of soil characteristics. To improve the accuracy of soil erodibility factor 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 global gridded datasets and obtain more accurate estimates of soil erodibility. This will help in developing better soil conservation and erosion management strategies that can effectively protect the soil and the environment.

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Compliance with Ethical Standards

The authors declare that they have no conflict of interest.

Data Availability

The dataset and shapefiles are available as ISED (Indian Soil Erodibility Dataset) with this repository: https://zenodo.org/record/6505511

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