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Mapping soil erodibility over India

Ravi Raj [a], Manabendra Saharia [a,b,*], Sumedha Chakma [a]

[a] Department of Civil Engineering, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India
[b] Yardi School of Artificial Intelligence, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, 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 the Soil erodibility factor, denoted by the 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 the 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.

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 spatiotemporal 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 fewer input datasets, are robust, and are 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 the soil erosion problem, which is currently missing over India. In this study, the soil erodibility factor has been modeled 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

* Corresponding author at: Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India.
E-mail address: msaharia@iitd.ac.in (M. Saharia).

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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 have 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 the K-factor for tropical regions using SOM, soil permeability, and soil texture data. Although these models estimated 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 modeling 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 the 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.

Soil erodibility is the property of soil that should be calculated in situ for greater accuracy to estimate soil erosion losses. But experimental estimate of K-factor is limited considering the larger study region like India. In the previous sections also, it was mentioned that the empirical equations and models have been used worldwide to estimate soil erodibility factor considering the time consumption and cost of the project for larger areas. However, the selection of the model or equation is quite important for better accuracy of the simulated erodibility factors with the field observations considering the availability and nature of the data for the study region. The current emphasis of the world's research community is on the development of composite models that will hopefully reproduce the field-based soil erodibility factor values with a higher degree of precision globally. RUSLE's Nomograph with other models like EPIC and erodibility indices like CR, MC and CLOM index had been estimated at the watershed or regional scale across the world. In this research we mapped soil erodibility factors and its indices over the national boundary of India which was not yet been explored.

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 the Ri-Bhoi district of Meghalaya. In the 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) have 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 helpful in developing soil conservation and erosion mitigation plans.

In this study, we estimated soil erodibility factors over a national scale using RUSLE Nomograph (K_{NOMO}) and EPIC (K_{EPIC}) models. In addition to this, a comprehensive statistical analysis of the soil erodibility map was carried out so that its distribution over the national territory could be visualized in terms of the different soil types, textures, and percentage ranges of erodibility values. Erodibility indices like CR, MCR, and CLOM indices were estimated over India, and their sensitivity to soil erodibility was also checked. The erodibility index which showed the greater correlation with the K-factor was mapped in scatter plot. CLOM index reflects the availability of organic matter in soil which provides strength against the erosive forces. A susceptibility to erosion map was also produced considering the CLOM values across the nation. 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 it is 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 is shown in Fig. 1.

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%)). The 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% of water bodies, 0.67% of 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 the percentage of sand, silt, clay, soil organic carbon (SOC), soil organic matter, soil texture class, soil structure code (SSC), and soil permeability code (SPC). The 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 particle 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 the national scale.

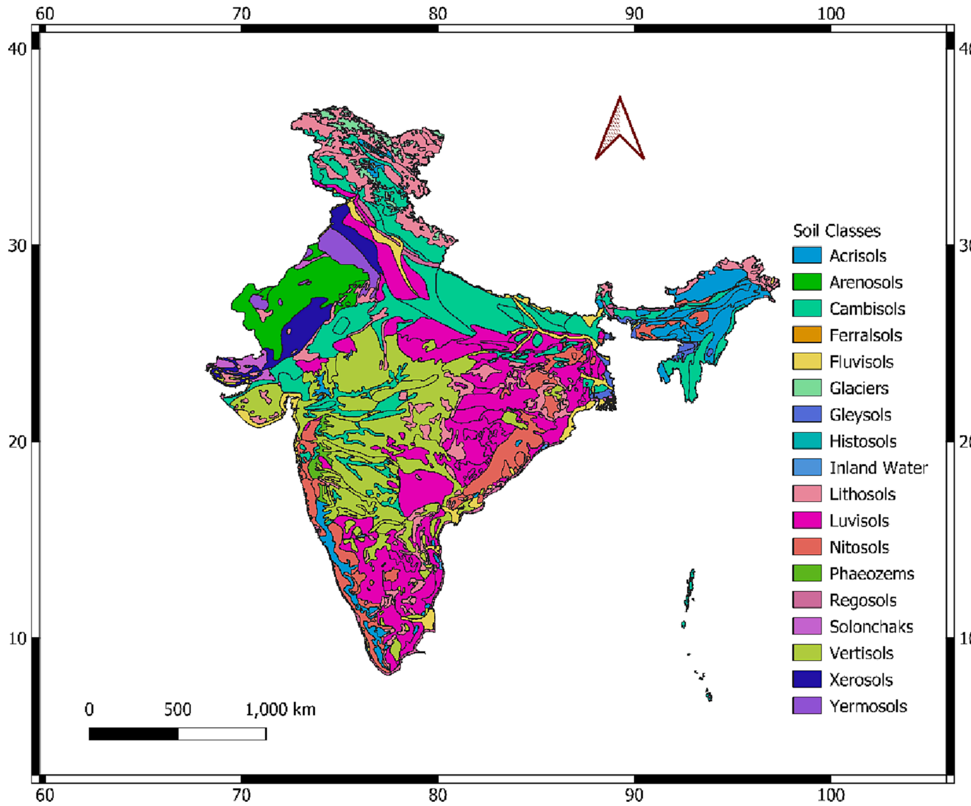

Fig. 1. Soil classes of India (Source: FAO-UNESCO Soil Map of the World).

2.2.1. *Soil particles properties*

SoilGrids is a platform where soil profile datasets are compiled using machine learning methods to produce digital soil maps over the globe. Global soil profile datasets are available at WoSIS (World Soil Information Service). More than 230,000 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 the SoilGrids website. In this research, properties of soil particles, such as the content of silt, sand, clay, and soil organic carbon (SOC), were used. These datasets were downloaded using Google Earth Engine (GEE) at 250 m resolution for the entire India. The units of contents of sand, clay, and silt are the same, i.e., weight percentage (g/g), but the unit of SOC is in g/kg. Soil organic matter (SOM) was 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 on very fine fraction of sand was also not available at the 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 the 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 be assigned to 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.

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.

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

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

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.

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 Fig. 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).

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

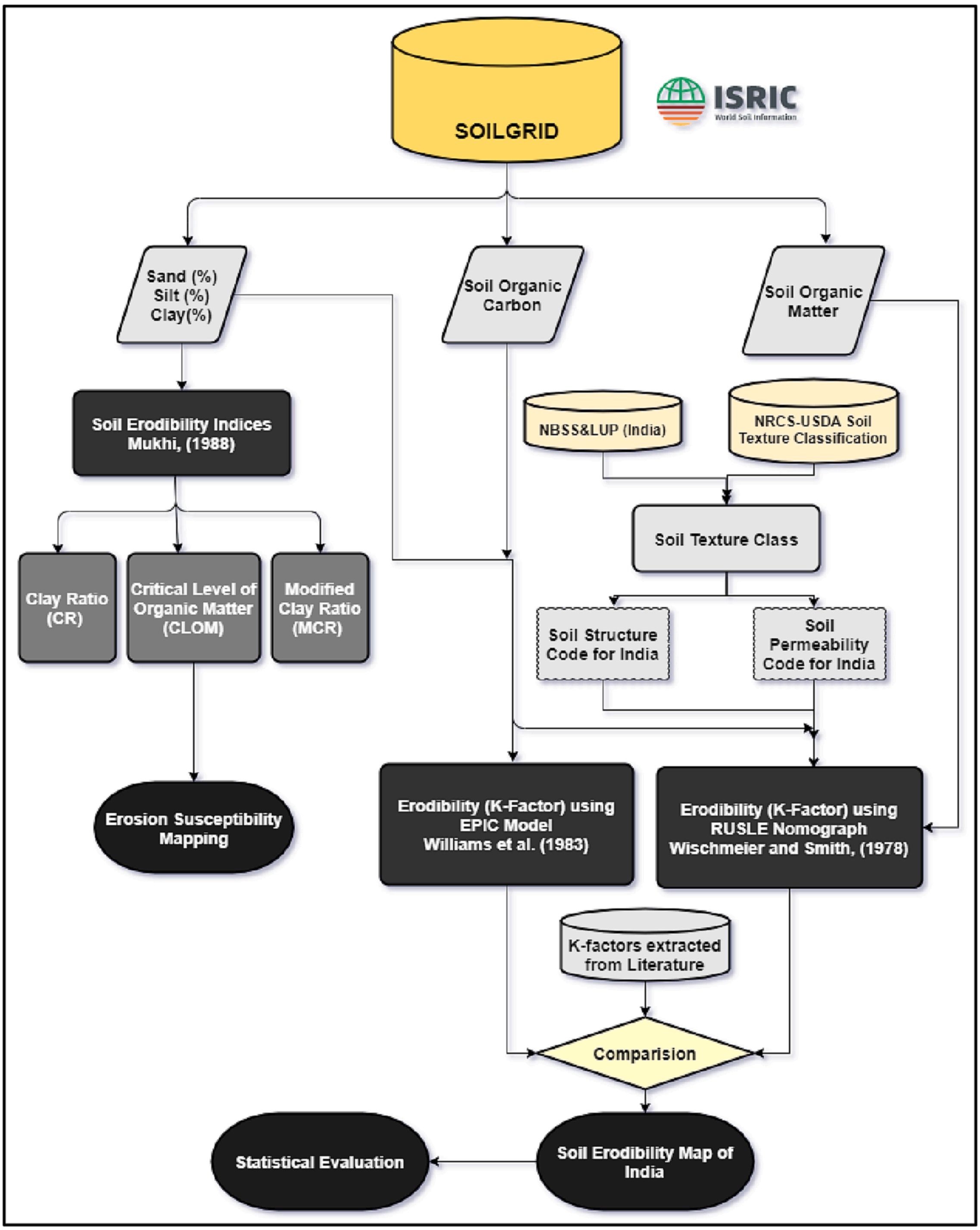

Fig. 2. Workflow methodology for soil erodibility mapping over India.

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 have 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 Eq. (1).

$$K_{NOMO} = 0.1317\{(2.1M^{1.14}*10^{-4}*(12 - SOM) + 3.25(s-2) + 2.5(p-3))\tilde{A}\cdot 100\} \tag{1}$$

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, converts the unit of K-factor into SI unit, i.e., t-ha-h/ha/MJ/mm. The percentage of very fine sand (vfs) was calculated as 20% of the content of the sand. The nomograph equation was defined for those types of soil profiles 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 the EPIC model approach (K_{EPIC}) is dependent on the percentage of soil particle size (sand, silt, and clay) and soil organic carbon (SOC) only, expressed as shown in Eq. (2).

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

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, converts 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, the higher the clay ratio, and harder it is to detach the soil particles by external forces (Bouyoucos, 1935). The clay ratio is inversely proportional to the K-factor. Clay ratio was further modified by introducing the 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 Eq. (3) and Eq. (4) simultaneously.

$$CR = \left\{\frac{(\%SAND + \%SILT)}{\%CLAY}\right\} \tag{3}$$

$$MCR = \left\{\frac{(\%SAND + \%SILT)}{(\%CLAY + \%SOM)}\right\} \tag{4}$$

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 Eq. (5).

$$CLOM = \left(\frac{SOM}{CLAY + SILT}\right) \tag{5}$$

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. The availability of organic matter in the soil provides strength against soil erosion. It implies that the lower the CLOM values, the greater the vulnerability to soil erosion. Best correlated erodibility index was also plotted against the K-factor to visualize its variation corresponding to soil texture classes defined by NBSS & LUP, India.

3. Results and discussions

3.1. Erodibility factors

Soil particle parameters (percentage of sand, silt, clay, structure code, permeability code, SOC, SOM, and vfs) were used to estimate K-factors using Nomograph and EPIC model approaches. Soil erodibility factor maps (K_{NOMO} and K_{EPIC}) have been shown in Fig. 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. Detailed statistics of K-factors have been shown in Table 4.

The Nomograph approach for calculating K-factor allows the SOM to be less than or equal to 12 as mentioned in Eq. (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 Eq. (1) also affected negatively by 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 for reflecting negative values of the K-factor using the Nomograph method. These negative values were only 0.22% of the total pixels in the study region. It was observed that the negative values ranged from 0 to −0.017 and occurred in the regions having soil types with blocky, platy, massive, medium, or coarse granular soil particles, which have higher resistivity to soil erosion. To rectify these negative values, the modulus of the K-factor was incorporated. Lower values of the K-factor reflect higher resistivity against soil erosion.

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

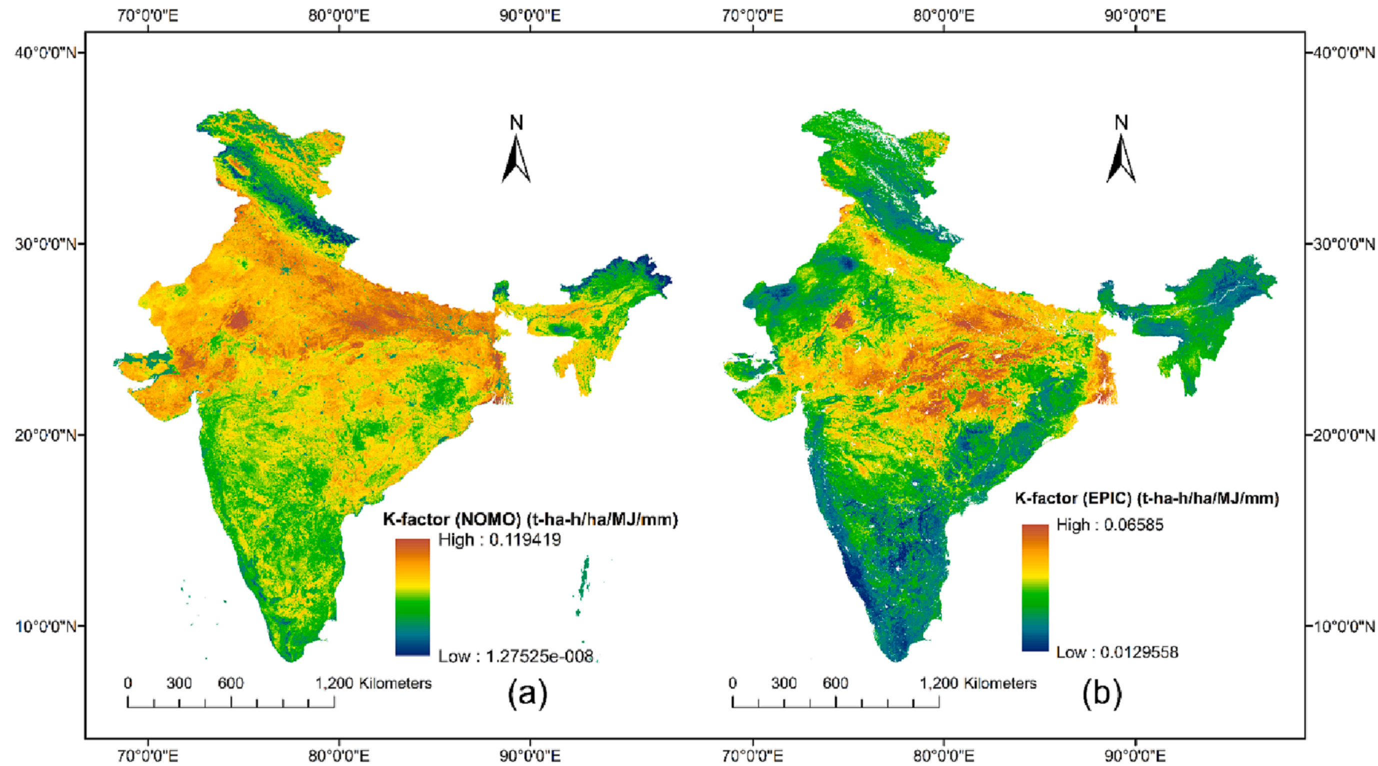

Fig. 3. (a) and (b) Soil erodibility factor maps (K_{NOMO} and K_{NOMO}) over India using RUSLE Nomograph and EPIC models, respectively.

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

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 the EPIC model had overestimated the soil erodibility values than that of the Nomograph model. A difference map had been created between K_{EPIC} and K_{NOMO} maps, which has been shown in Fig. 4. K-factor value differences range 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% of values were overestimated using the EPIC model. This could be due to the parameters taken to estimate soil erodibility by both models. The EPIC model does not count the structure and permeability codes, while these two parameters are associated with the Nomograph model and create an adequate impact on the soil erodibility estimated using this model. Taking into account soil's structural and permeability factors, it offers additional information about the qualities of soil particles that is crucial for preventing soil erosion by influencing soil erodibility values.

3.2. Erodibility indices

Clay ratio (CR) and Modified Clay Ratio (MCR) were calculated using the percentage content of sand, silt, clay, and SOM present in the soil samples, which have been shown in Fig. 5(a) and (b). India's average CR and MCR were calculated as 2.32 and 2.07, while the maximum was 22.81 and 17.42, respectively. The differences in the spatial variation of these two indices could be visualized in Fig. 5(a) and (b), where higher values (greater than5) were spotted in the northern upper side of the study region (Jammu and Kashmir, Himachal 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 the modified clay ratio, which reduces the value of MCR in comparison to CR.

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, Himachal Pradesh, and a few regions of Rajasthan and Jammu and Kashmir; while lower values were spotted in the regions of Central India (Fig. 5 (a)). Apart from the regions covered by higher CR values, MCR also covered major portions of Rajasthan, 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 (Fig. 5 (b)).

The critical level of organic matter (CLOM) ratio was calculated using the soil particles parameter datasets over India shown in Fig. 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 Fig. 6. Only border areas of Arunachal Pradesh, Sikkim, Uttarakhand, Himachal Pradesh, and some regions of Jammu and Kashmir were identified as stable regions due to soil erosion considering the higher CLOM values. A major portion of the country (greater than80%) areas were spotted as highly susceptible regions due to soil erosion having lower CLOM values.

3.3. Relationship between K-factors and erodibility indices

Erodibility indices (CR, MCR and CLOM) had been used as an alternative 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

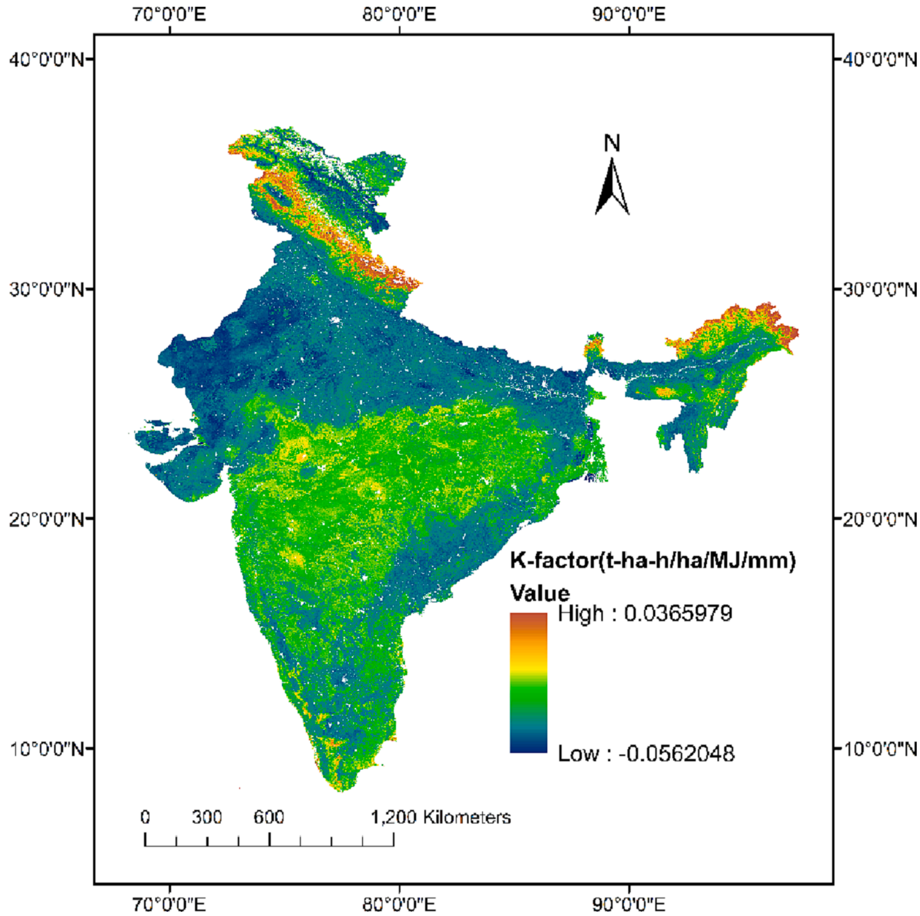

Fig. 4. Difference map of K-factor estimated using EPIC model compared with Nomograph model.

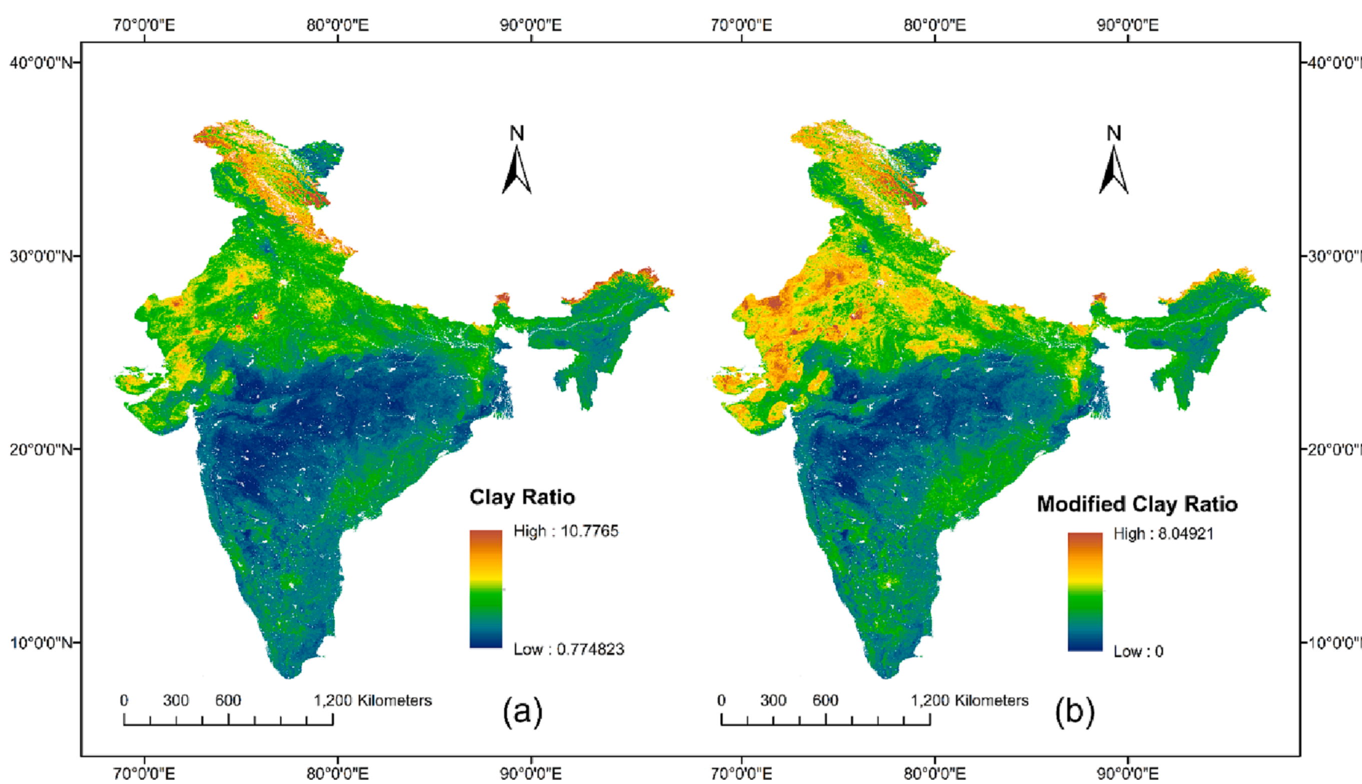

Fig. 5. (a) and (b) Clay Ratio (CR) and Modified Clay Ratio (MCR) Maps over India.

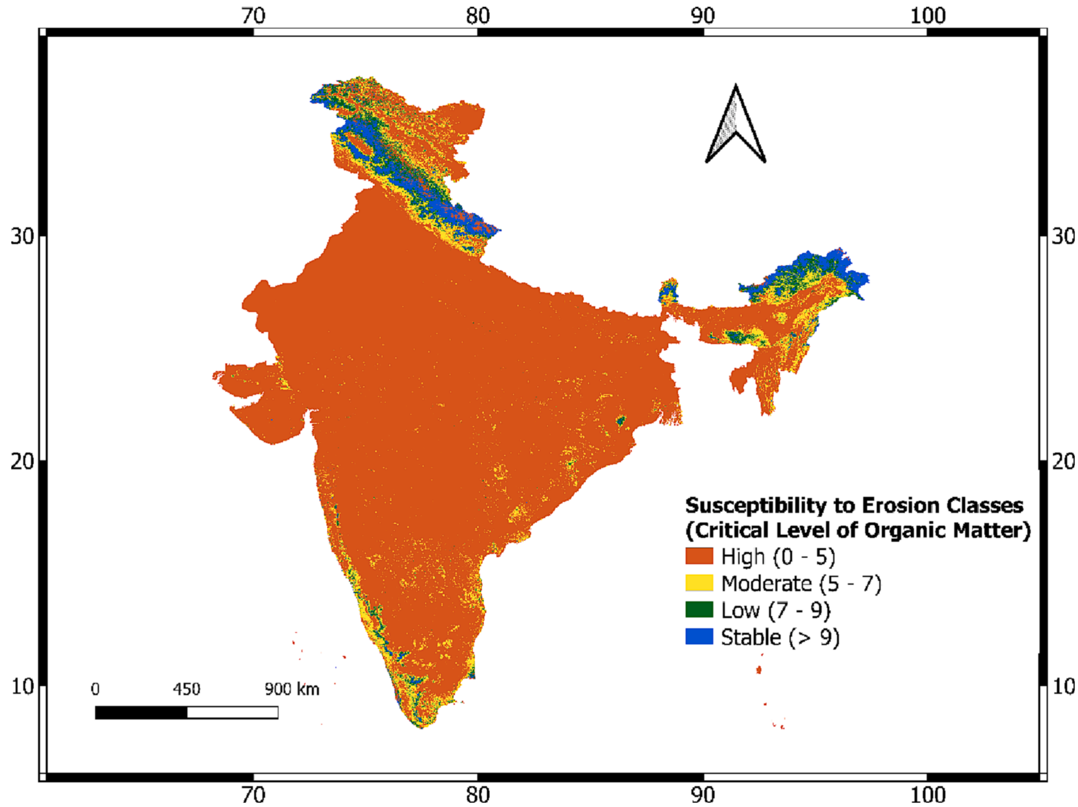

Fig. 6. Susceptibility to soil erosion classes based on Critical Level of Organic Matter (CLOM) values.

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

calculated among erodibility indices and K-factors which is shown in Table 5. Erodibility factors computed using both methods gave a correlation coefficient of 0.64 despite showing overestimation in calculating the K-factor by the EPIC method. It was observed that only CR with MCR and CLOM index with KNOMO were correlating with better accuracy having Pearson's correlation equals 0.95 and −0.73, respectively. A negative correlation shows that if the value of the CLOM index increases, the values of K_{NOMO} decrease, 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. The best-correlated erodibility (CLOM) index was plotted against the K-factor to visualize its variation corresponding to soil texture classes defined by NBSS & LUP, India, as shown in Fig. 7.

3.4. Distribution of soil erodibility (K-factor)

India's average soil erodibility factors (KNOMO and KEPIC) are estimated at 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. The KNOMO and KEPIC factors were compared with the few existing studies conducted in India. Bera (2017) estimated soil erosion for the Gumti river basin of Tripura, India, where he also estimated soil erodibility values. Olaniya et al., (2020) also estimated K-factors for Ri-Bhoi district of Meghalaya, India. The authors collected these two K-factors, 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 methods.

By analyzing the values of K-factors from Table 6, it was observed that K_{NOMO} shows a 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 the 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. The total number of pixels available in the K-factor map of India, were grouped in five ranges shown in Fig. 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).

To make the study usable at the policy level, the K_{NOMO} map was

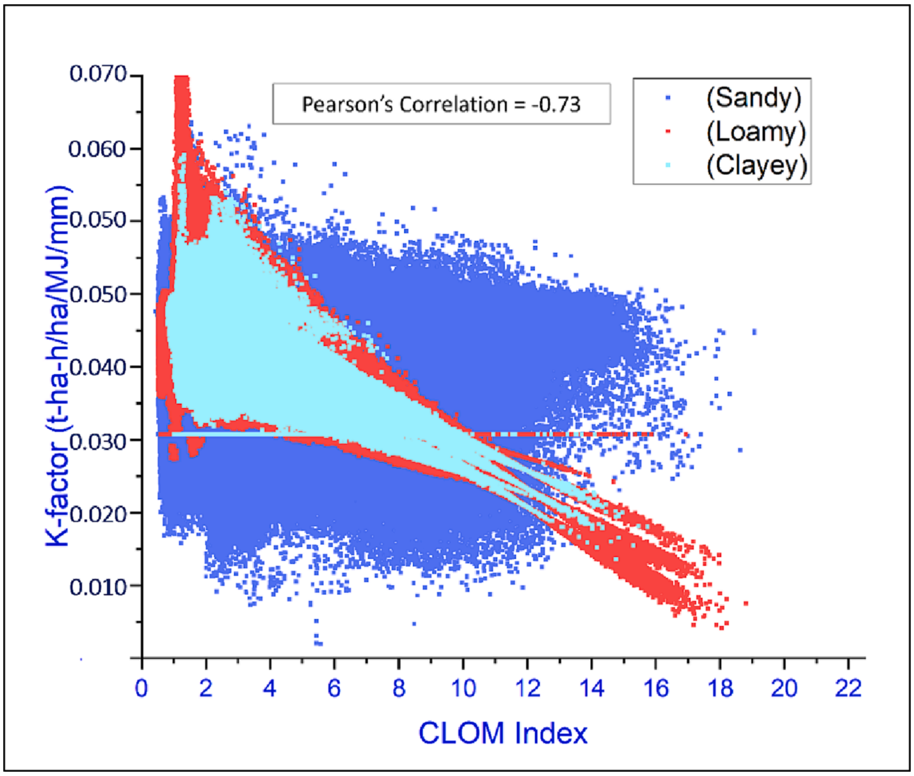

Fig. 7. Scatter plot between K-factors (t-ha-h/ha/MJ/mm) and Critical Level of Organic Matter (CLOM) index highlighting for major soil texture classes (Loamy, Clayey, and Sandy).

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

used to extract average K-factor values for the soil classes defined by FAO-UNESCO. Considering the soil classes across the country, the 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 the Xerosols soil type was most susceptible to soil erosion having the 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 referred to in Fig. 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 the 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.

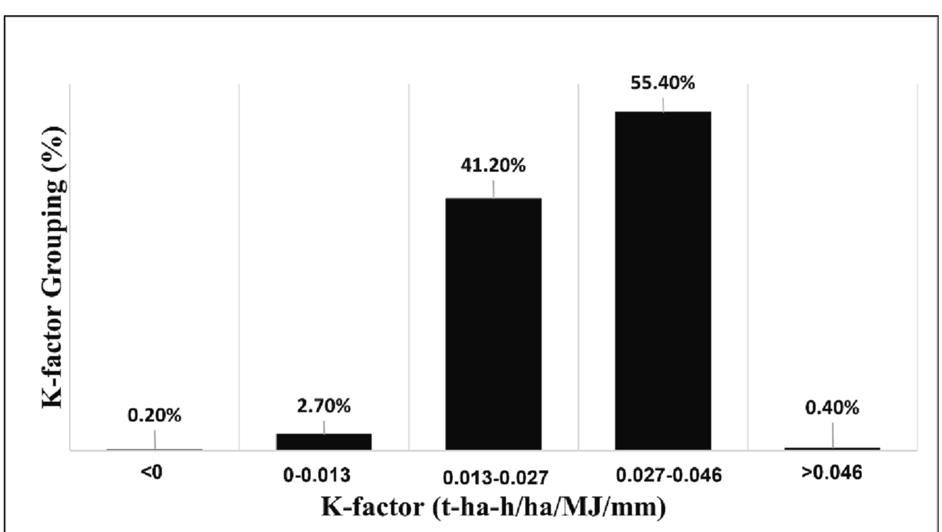

Fig. 8. Distribution of the range of K-factors (t-ha-h/ha/MJ/mm) grouped in percentages in the form of bar-chart.

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 factors in the Indian region. High-resolution (250 m) input datasets for soil erodibility estimation from SoilGrids were 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 the Nomograph model (K_{NOMO}) show better agreement with the past studies.
- National average soil erodibility factors 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% K-factor values 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 the lowest average K-factor (0.011 t-ha-h/ha/MJ/mm) while the Xerosols soil type was most susceptible to soil erosion having the 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 also been compared with the K-factors (K_{NOMO} and K_{EPIC}) to check the relationships of these indices with the K-factor. It was observed that only the CLOM index showed a better correlation (Pearson's correlation = -0.73) with K_{NOMO} in the Indian condition.
- A susceptibility to soil erosion map was also created based on the 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 factors 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 in India. Since extensive local ground measurements were unavailable for this study, global gridded datasets were utilized instead. However, these datasets have their own limitations, depending on the statistical approaches used to interpolate spatial point 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.

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.

Declaration of Competing Interest

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.

Data availability

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