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Advances in the quantification and prediction of soil erodibility: A review

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Abstract
Soil erosion is a major environmental concern that accelerates land degradation, reduces agricultural productivity, and threatens ecosystem stability. At the core of erosion studies lies soil erodibility, which describes a soil's inherent susceptibility to detachment and transport by wind or water. This review critically examines the key factors influencing soil erodibility, including soil texture, organic matter, structure, and vegetation cover. It synthesizes existing literature on various methods used to assess erodibility, ranging from traditional laboratory and field techniques to advanced remote sensing and geospatial approaches. Recent progress in predictive models and erosion risk assessments is also reviewed, particularly in the context of climate change and shifting land use patterns. By integrating insights from current research, this paper aims to provide a comprehensive understanding of soil erodibility and inform the development of effective soil conservation strategies and sustainable land management practices.

Keywords: Soil erosion; soil erodibility; USLE; remote sensing; predictive modelling; conservation strategies

Introduction
Soil erosion is one of the most pressing environmental challenges faced globally, contributing to the degradation of valuable land resources and threatening food security (Lal, 2001; Pimentel *et al.*, 1995) [60, 81]. The process of soil erosion, which involves the detachment and transport of soil particles by wind, water or other agents, is influenced by a variety of factors that determine the vulnerability of soil to erosion (Morgan, 2005) [68]. These factors, collectively referred to as soil erodibility, are intrinsic soil properties such as texture, structure, organic matter content and permeability, as well as extrinsic factors like climate, land cover and human activities (Renard *et al.*,1997; Vigiak *et al.*, 2016) [90, 111]. Understanding soil erodibility is fundamental for assessing the risk of erosion, developing effective soil conservation practices and implementing land management strategies that safeguard soil resources (Boardman and Poesen, 2006) [11]. Over the years, research has shown that soil erodibility is a dynamic characteristic that can vary significantly depending on environmental conditions and land use practices (Schmidt *et al.*, 2001; Govers *et al.*, 2007) [94, 35]. For instance, soils under intense agricultural use or improper land management are often more prone to erosion, leading to the depletion of topsoil and a reduction in soil fertility (Lal, 2001; D'Odorico *et al.*, 2013) [60, 19]. Conversely, soils in well managed or naturally vegetated ecosystems tend to exhibit greater resistance to erosion (Gobin *et al.*, 2009) [34]. Various methods and models have been developed to quantify and predict soil erodibility, ranging from laboratory tests and field observations (Wischmeier and Smith, 1978) [117] to more recent advancements such as remote sensing and computational models (Foster *et al.*, 2002; Verheijen *et al.*, 2009) [30, 109].
This review aims to provide a detailed synthesis of the factors influencing soil erodibility, the methods used to assess it and the ways in which erodibility can be mitigated through land management practices. By consolidating current knowledge, this paper seeks to inform strategies for minimizing soil erosion and promoting sustainable land use practices that preserve soil health for future generations (FAO, 2011; Montgomery, 2007) [26, 67].

Concept and Significance of Soil Erodibility

Soil erodibility, a key concept in erosion prediction models, represents soil susceptibility to erosional processes (Bryan *et al.*, 1989) [15]. However, the concept has limitations, as different soil properties determine erodibility for each erosional subprocess, and it cannot be uniquely defined by a few properties (Bryan *et al.*, 1989) [15]. It is typically measured in experiments using equipment such as The Erosion Function Apparatus (EFA), hole erosion test (HET), and Erosion Test (JET) (Philippe and Benahmed, 2024) [80]. According to (Philippe and Benahmed, 2024) [80], it is typically a function of the onset of erosion and the rate of erosion. In (Bao, 1999) [4] research, this concept has been applied extensively to various situations, such as in China, where a local definition was developed to meet local demands. Field tests have also been conducted to determine the erodibility values of certain soil types, such as Hapludox in Brazil (Bertol *et al.*, 2007) [9]. Soil erodibility is the sensitivity of soil particles to raindrop impact and transport by breakdown and runoff (Renard *et al.*, 1997) [90]. According to (Lal, 1994) [59], conditions such as particle size, the stability of the structure, organic matter, soil chemistry, and the movement of water influence such processes. The soil erodibility parameter quantifies the average quantity of soil lost per unit rainfall erosivity on a single plot (Zhang *et al.*, 2004) [119, 120]. Soil erodibility quantifies the manner in which the soil responds to rainstorm energy, balancing the influence of rainfall, water absorption, and runoff on soil erosion (Bonilla and Johnson, 2012) [12]. Soil erodibility is a result of properties caused by numerous factors, but some of these only have a direct correlation with types of soil (Veihe, 2002) [108]. Soil erodibility is a complex term caused by numerous conditions. Conditions influencing how easily the soil erodes by water and wind are properties that do not change significantly with time (e.g., soil texture, calcium carbonate, salinity, cation exchange capacity, moisture content, and organic content) and properties that change rapidly (e.g., microtopography, soil crust, surface bulk density, and aggregate size distribution) due to climate or management, which affect daily soil erodibility. Practically every property of the soil can influence the manner in which it responds to erosion, but as Lal (1990) [58] wrote, there is no one, simple soil measure that can reasonably describe how soil erodibility functions. Some factors like soil texture, aggregation, consistency, and shear strength normally contribute significantly to how the soil will respond to erosion, whereas other properties only indirectly contribute (Fox, D. M., and Bryan, R. B., 2000) [31]. People previously thought that soil erodibility was nearly the same for a specific soil type. But after much study, more researchers have found that soil erodibility is relative and depends mainly on a range of soil characteristics that change over time and in response to human activities. Soil erodibility depends on the type and strength of erosive force, so the erosive force conditions need to be considered when deciding the soil erodibility index. The erodibility of different soils in different locations and land use categories has been studied, as has been explained earlier. These studies revealed that the soil erodibility is different from place to place. You can see clearly that you cannot compare the erodibility of different soils because this index is not capable of representing the impact of soil qualities directly. Erodibility determining properties like soil aggregation and shear strength are influenced greatly by weather factors like regimes of rainfall and frost, and they have regular fluctuations according to seasons. They can also display sudden changes over shorter intervals of time as a result of minor variations in soil water content, organic matter, microbial activity, aging, and pressure effects on the structure of the soil (Fox, D. M., and Bryan, R. B., 2000) [31]. Extensive changes in soil conditions are brought about through gradual drying during storms. The manner in which the soil aggregates seem to influence the ease with which it will dry out (Kuhn, N. J., and Bryan, R. B., 2004) [56]. It varies with varying agricultural practices, land use changes, and the incidence of wildfires.

Factors Affecting Soil Erodibility

The characteristics of the soil, as well as the land use and topographic features, alongside the climate, determine soil erodibility. A notable factor impacting soil erodibility is the organic matter content, as increased situations tend to reduce erodibility (Parwada and van Tol, 2017; Zhu *et al.*, 2019) [79, 122]. Also, the soil texture, structure, and its chemical composition are of considerable significance (Belasri and Chaib, 2017) [5]. Likewise, erodibility is varied by land use, with farmland being more susceptible than grassland (Zhu *et al.*, 2019) [122]. It's known that erodibility changes over time or with foliage restoration, but within the environment of restoration trouble, soil erodibility was the higher from 2006 to 2011, while other period (1999-2005 and 2012-2016) were comparatively lower. (Zhu *et al.*, 2019) [122]. Soil erodibility charts can be fulfilled with Geographic Information System (GIS), which help in defining spatial patterns of soil erodibility (Belasri and Chaib, 2017) [5]. This allows determination of places that need more attention for conservation strategies. Pitch as part of geomorphology is a top factor that influences the k factor of soil erodibility, and sharper pitch has stronger donation by adding face inflow rapidity. This leads to faster soil movement downstream compared to uphill (Meshesha *et al.*, 2016) [66]. K is significantly reduced by thick foliage combined with high violent downfall and mean periodic temperature (Correa *et al.*, 2016) [18]. (Zhang *et al.*, 2018) [114] quantitatively measure the impact of different species of shrubs and meadows planted on steep pitches of gully and how they affect six pointers of erodibility and integrated erodibility indicator (IEI). Other important regiment as changers of erodibility include the controlled soil water and face runoff, which prove the notion that type of foliage both active and unresistant restoration dictates soil stability (Zhang *et al.*, 2018) [114]. (Wynn and Mostaghimi 2006) [118] explain how a number of interrelated factors control the erodibility of soil. These correspond of soil bulk viscosity, antecedent humidity before rain, soil texture, snap/ thaw cycles, and viscosity of different root sizes. These all control the critical shear stress and soil strength.

Measurement and Estimation Techniques of Soil Erodibility

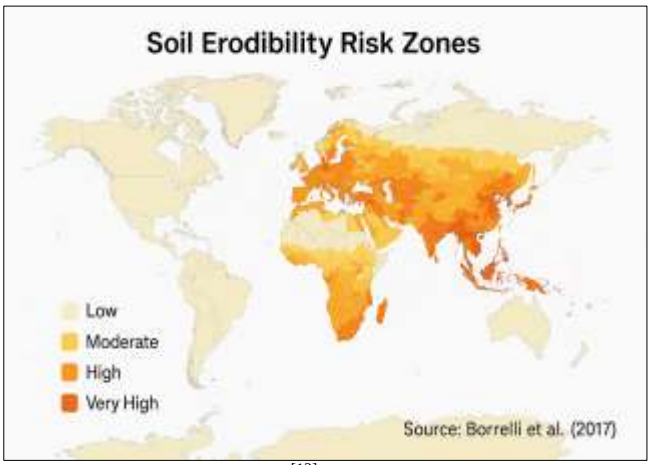
The evaluation of soil erodibility is essential for locating and mollifying erosion related issues. The operation of Revised soil loss equation (RUSLE) in Geographic information system (GIS) systems is one of the soil erodibility assessment styles that have been developed (Ferreira 2010) [28]. The operation of multivariate statistical analysis of soil characteristics and geological data helps to

identify regions with high erodibility (Nosrati *et al.*, 2011) [75]. Aggregate stability is the stylish index of soil erodibility, and new technologies, similar as computer backed tomography, hold pledge for further thorough evaluations (Benaud *et al.*, 2021) [6]. Prophetic models of soil erodibility, grounded on circular field measures, are extensively accessible due to the high cost of direct measures. These models, still, need to be tested to confirm their connection to the study areas. An illustration of such a model tested for connection to specific soils is the one handed by Sharpley and Williams (1990) [96], which is valid for earthy beach and complexion soils (Anache *et al.*, 2016) [1]. Research conducted with USLE and EPIC models for soil erodibility estimation concluded that vertisols have lesser erodibility (M. Djuwansah and A. Mulyono, 2016) [24]. The Nomograph system was more precise than was measured when calculating the soil erodibility factor (K-factor) in India. The exploration created new erodibility indicators similar as complexion rate (CR), Modified complexion rate (MCR), and Critical position of Organic Matter (CLOM) to study how they express soil erodibility (Ravi Raj *et al.*, 2023) [89]. (R. Rickson *et al.*, 2021) [91] demonstrated that aggregate stability is the strongest predictor of soil erodibility, but the selection of styles to quantify it should take into account the varied forces and breakdown processes to which soil summations are subordinated in the field. R. Loch and C. Rosewell, 1992) [63] proposed some laboratory styles to estimate soil erodibility (K factor) for the Universal Soil Loss Equation. They first advised K by using the Wischmeier nomograph from different kind's data, including dispersed, non-dispersed, and original beach size distributions. They also acclimated the K factor grounded on the average viscosity of wet deposition patches larger than 0.100 mm for one system. In the exploration work of (J. A. Anache, *et al.*, 2016) [1], it was proposed that the Sharpley and Williams (1990) [96] model was the stylish to estimate soil erodibility (K-factor) in the exploration area. They employed circular styles to estimate soil erodibility (K-factor) rather than direct field measures. They compared the results of these circular styles with factual soil characteristics, K-factor values, and available data. (J. E. Denardin, 1990) [22] discovered the erodibility factor for 31 Brazilian and 46 USA soils using physical and chemical parameters. The erodibility indicators were determined in the field under natural downfall and artificial downfalls and were employed in correlation and retrogression analysis. The retrogression model grounded on soils from Brazil and the USA had a veritably high measure of determination (R^2 = 0.9767) and low standard error, indicating it was veritably prophetic of soil erodibility for numerous soil types. (T. C. Olson and W. H. Wischmeier 1963) [76] constructed a table listing values of the soil erodibility factor (K) for 20 soils. These may be used to estimate the erodibility of other soils. The K factor estimates the average loss of soil per unit of the erosion indicator (R) from a continued free face on a pitch of 72.6 bases in length and 9 percent inclinations.

Modelling Approaches for Soil Erodibility

According to (Renard *et al.*, 1997) [90] Empirical models like RUSLE are commonly used due to their simplicity and adaptability across various land uses. However, they often rely on average conditions and static parameters such as the K-factor, which may underrepresent the temporal and spatial variability of erosion processes. Despite these limitations, revised universal soil loss equation (RUSLE) remains the foundation for erosion modelling in conservation planning. (Nearing *et al.*, 1990) [74] Suggested the Water Erosion Prediction Project (WEPP) model provides a physically based, daily time step simulation of hydrologic and erosion processes, offering a more realistic representation of soil erodibility over time. It accounts for rainfall, infiltration, vegetation cover, and tillage practices, making it highly suitable for field to watershed scale erosion assessments. According to (Morgan *et al.*, 1998) [70] the European Soil Erosion Model (EUROSEM) models rainfall induced soil erosion by simulating detachment, transport, and deposition of sediment particles during storm events. It emphasizes raindrop impact, runoff generation, and sediment transport capacity, offering better short-term predictions in event-based studies. Also, machine learning models such as Random Forest (RF) and Support Vector Machines (SVM) have been increasingly applied to predict soil erodibility. These models can handle high dimensional, nonlinear relationships between soil properties (e.g., texture, pH, organic carbon) and land characteristics. Their accuracy significantly outperforms classical models when trained on sufficient data (Dinh *et al.*, 2021) [23]. Artificial Neural Networks (ANNs) have demonstrated high predictive power in estimating soil erodibility (K-factor) from remote sensing and in-situ data. Their ability to learn complex patterns makes them useful in modelling erodibility across diverse land uses, especially in tropical and semi-arid regions (Fernández *et al.*, 2023) [27]. Geographic Information System (GIS) modelling with remote sensing facilitates the production of large maps indicating where erosion risk is high, facilitating easier evaluation of erosion in areas with scarce field data. The technique assists in the identification of areas with highest erosion and the planning of means to mitigate it (El Jazouli *et al.*, 2017) [25]. Integration of simple models with AI techniques or geospatial tools results in improved and large-scale evaluation of soil erodibility. Such models integrate traditional model knowledge and the robust predictions of machine learning, rendering them more trustworthy in data scarce locations (Preetha and Joseph, 2025) [86]. Application of global soil and climate data has been proven to enhance sediment quantity and erodibility prediction in large watersheds. These global data sets perform at times better than local data since they correct for climate more thoroughly, particularly in regions influenced by seasonal changes in rainfall (Vigiak *et al.*, 2011) [110]. Regression models targeting soil texture, structure, and organic matter continue to be widely used to estimate the K-factor. Although such models are straightforward, they are of immense utility in areas where sophisticated modelling tools are unavailable. They, however, become less accurate as soil becomes highly varied in composition (Vaezi *et al.*, 2011) [107]. WEPP simulations indicate that rainfall variability, cover crops, and soil moisture during various seasons have significant impacts on soil erodibility, supporting the use of dynamic models for enhanced prediction and conservation planning (USDA-ARS, 1995) [106]. Deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are beginning to be used to predict soil erosion. They are capable of processing detailed satellite data and varied soil moisture patterns to yield improved models (Polovina *et al.*, 2024) [83]. Experiments have shown that

sediment yield predictions are heavily dependent on the K-factor. This suggests that the right methods should be chosen for estimating erodibility in soil erosion models to reduce uncertainty in conservation planning. Ensemble learning models combine predictions from different base learners and have been found to be superior to single model approaches, especially when the terrain is complex and climate soil interactions are intricate. These models are stable when data inputs are variable or uncertain (Fernández *et al.*, 2023) [27]. It is important to calibrate and validate erosion models using field observed data to improve the accuracy of predictions, especially where land cover and land forms are diverse. Field checking enhances confidence in model results and allows for targeted action (Sinha and Eldho, 2021) [99]. Coupling vegetation indices (e.g., NDVI) and terrain features from remote sensing with erosion models has helped identify areas prone to erosion, and conservation planning has become more specific and effective (El Jazouli *et al.*, 2017) [25]. Sensitivity analyses have shown the importance of accurate K factor estimation since a 10% change in the K factor can result in a 25% change in sediment yield predictions (Jisha *et al.*, 2022) [49]. GIS based machine learning techniques have also enabled the generation of detailed soil erosion risk maps, which are extremely useful in monsoon prone areas for planning conservation strategies (Chakrabortty and Pal, 2023) [17]. New global datasets incorporating factors such as saturated hydraulic conductivity have greatly improved the accuracy and reliability of soil erodibility estimates on a large scale (Gupta *et al.*, 2024) [37]. Finally, ensemble learning models, which combine several machine learning approaches, have fared better than single model approaches under changing conditions. These models improve robustness and find application in policy driven; region scale uses (Fernández *et al.*, 2023) [27].



(**Source:** borrelli *et al.*, 2017) [13]

Fig 1: erodibility risk zones across world

Impact of Soil Erodibility

An essential factor in assessing soil erosion and its effects on ecosystems and agriculture is soil erodibility. Research indicates that erodibility is significantly influenced by soil structure, with disturbed soil samples exhibiting erodibility that is up to ten times greater than that of undisturbed samples (Thomaz, 2024) [104]. Sediment load estimates in catchment scale modelling can be significantly impacted by the method used to estimate the soil erodibility factor (K), with global datasets possibly producing better results than local datasets because of climatic impacts. To identify slopes that are prone to erosion, soil erodibility studies have been conducted in Malaysia for both large scale areas using the Universal Soil Loss Equation (USLE) and small-scale areas using the Roslan and Mazidah Scale (ROM) (Derahman *et al.*, 2022) [21]. But determining soil erodibility can be costly and time consuming, which highlights the value of straightforward methods that don't require a lot of lab work. Assessing erodibility requires looking at the particular soil material at the surface because it varies significantly based on the crusting stage and biological activity. (Bissonnais and Darboux, 2007) [20]. Examined the erodibility of soil in wind and water erosion scenarios, emphasizing the significance of organic matter, texture, and structure. Found research gaps in non-agricultural land. The intricacy of soil erodibility and the necessity of taking into consideration a number of variables in predictive models were highlighted by the study. (Benavidez *et al.*, 2018) [7] Assessed the global applicability of the RUSLE model. Highlighted the limitations of the K factor and suggested local calibration. They made the case for adding more dynamic variables to erosion modelling tools in order to increase their robustness. (Batista *et al.*, 2023) [3] Used a soil thinning experiment to study erosion feedbacks. It was discovered that a self-reinforcing loop occurs when soil becomes more vulnerable to erosion in the future as organic matter and fine particles decline as a result of erosion. (Ojo *et al.*, 2023) [46] Carried out field tests on an alfisol utilizing vegetative barriers, mulching, and ridging as conservation techniques. Discovered notable decreases in soil erodibility, confirming the contribution of agronomic techniques to erosion prevention. (Jeloudar *et al.*, 2018) [48] Investigated how Iran's changing land use affected the erodibility of the soil. The effects of deforestation were highlighted by the discovery that conversion from forest to agriculture raised K-factor values by as much as 40%. Insights from China that demonstrate a high degree of spatial variability in K-values across various landscapes. Determined how soil physical characteristics affect erodibility using rainfall simulations in the Loess Plateau. Shown that weakly structured, low organic matter loess soils are especially susceptible to water erosion. (Shi *et al.*, 2012) [97] Examined the effects of watershed management in China's Three Gorges region. It was discovered that integrated land management techniques, such as terracing and reforestation, enhanced soil structural stability and decreased soil loss. (Karmaker and Das 2017) [52] Used genetic algorithms to estimate riverbank soil erodibility parameters like the erodibility coefficient and critical shear stress. The study demonstrated how machine learning can improve erosion modelling precision. Developed empirical formulas for K factor estimation across Chinese agricultural soils. They compared the performance of models and discovered that traditional approaches frequently overestimated soil erodibility. (Issaka and Ashraf, 2017) [47] Reviewed the impact of soil degradation on water quality, linking erosion with increased turbidity, nutrient runoff, and pollutant loading in surface waters, affecting aquatic ecosystems and drinking water quality. (Mandal *et al.*, 2023) [100] Evaluated erosion's impact on soil quality and crop yield in Himalayan regions. It was noted that erosion induced topsoil loss affects nutrient availability, soil biological activity, and overall agricultural viability. (Bhattacharyya *et al.*, 2007) [10] Presented a national study of soil deterioration in India.

Water erosion was identified as the most pervasive degrading process, affecting more than 100 million hectares and having important social and ecological repercussions. (Panagos *et al.*, 2015) [77] Using RUSLE2015 and high-resolution statistics, they modelled soil loss across the EU. Land cover, slope, and rainfall erosivity were found to be strongly associated with spatial K-factor variance. The findings helped shape EU soil conservation policy.

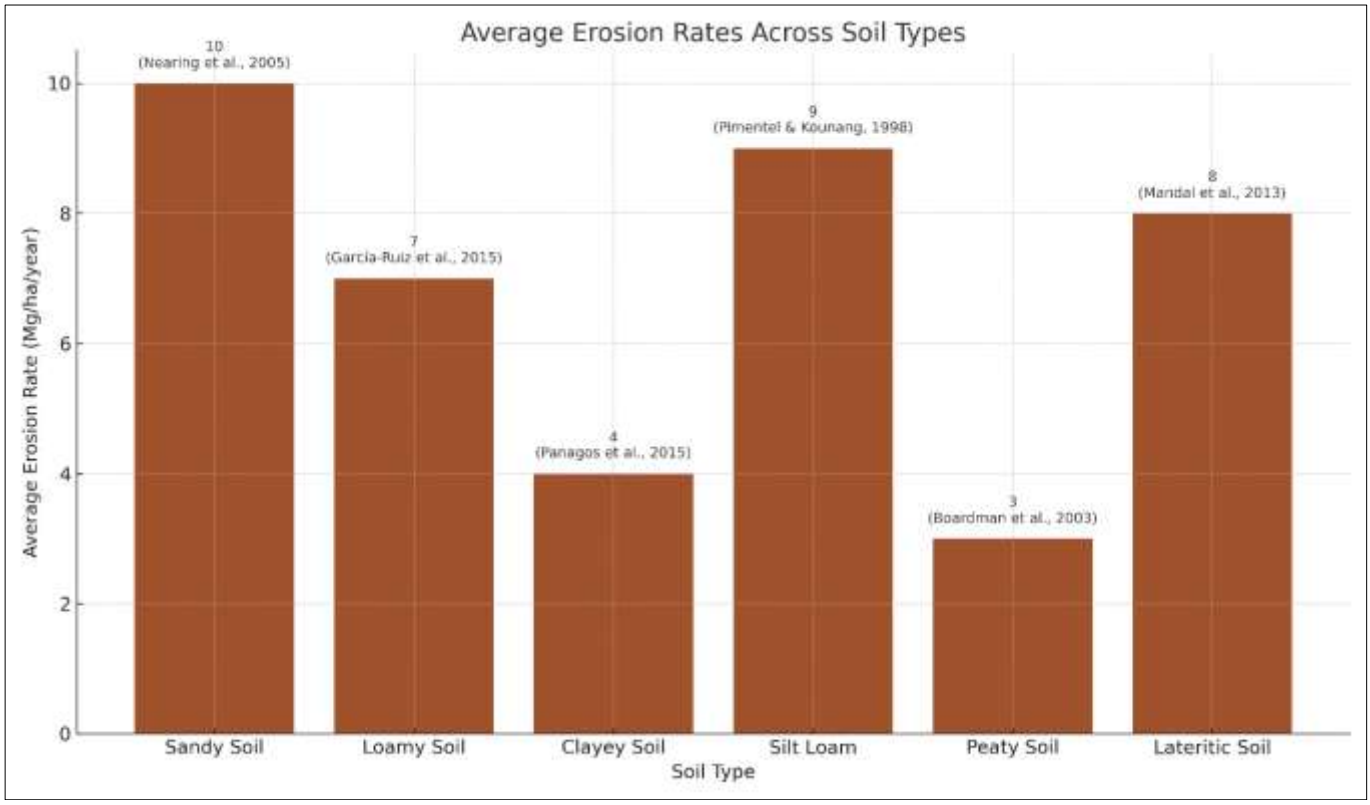


Fig 2: Average erosion rates across soil types

Mitigation Strategies for Soil Erodibility

Soil erodibility is directly dropped by conservation tillage ways like minimal tillage or no till agriculture, which maintain soil structure and lessen aggregate breakdown. No till systems can reduce erosion by over to 70 percent when compared to conventional ploughing, especially in regions with moderate to high rainfall (Lal, 2001) [60]. Common structural interventions that aid in water retention and slow deposition movement on steep pitches include terracing. In addition to stabilizing the geography, water retention which encourages the growth of foliage and ultimately lowers soil erodibility (Morgan, 2005) [68]. Both synthetic and organic mulching lowers evaporation and protects soil shells from the goods of rainfall. According to studies, depending on pitch and the quantum of downfall, organic mulch can reduce soil erosion by 40-70 percent. Soil erosion can be significantly reduced by enforcing agroforestry systems, which incorporate trees into geographies. Tree or plants reduce the impact of drops, while root systems ameliorate soil cohesiveness. Agroforestry has been shown to reduce soil erosion by further than 50 percent in tropical and semi-tropical regions (Nair, 1993) [72]. Compost, biochar, and gypsum are exemplifications of soil emendations that increase aggregate stability and water retention. By adding soil porosity and microbial exertion, for case, the operation of biochar has been demonstrated to drop soil erodibility (Gul *et al.*, 2015) [39]. Reforestation and the installation of buffer strips alongside aqueducts are exemplifications of catchment scale interventions that help lower deposition loads and safeguard submarine ecosystems. Specifically, riparian buffer zones can help up to 85 percent of soil loss by landing deposition before it reaches aqueducts (Mankin *et al.*, 2007) [64]. Agronomic, engineering, and socioeconomic approaches are all combined in integrated watershed management (IWM) to address erosion holistically and collaboratively. IWM has demonstrated efficacity in Indian surrounds, performing in notable increases in agricultural productivity and a 60 reduction in soil loss (Wani *et al.*, 2003) [115]. These days, erosion threat mapping and strategy planning heavily calculate on remote sensing and GIS technologies. Land directors can prioritize conservation sweats and apply focused interventions by relating high threat zones (Panagos *et al.*, 2015) [77]. For erosion mitigation programs to be successful over the long term, community involvement and policy support are essential. It has been demonstrated that furnishing growers with impulses and education to adopt conservation practices greatly increases perpetration rates and long-term goods (Enough and Shah, 1997) [87]. In addition to the extensively used structural and agronomic measures, a number of new and area specific ways have been developed to more successfully reduce soil erodibility. Crop rotation for cover operation contributes to the preservation of natural diversity and soil structure. Rotating crops with deep and shallow roots enhances nutrient cycling, organic matter content, and subsurface stability, all of which lower erodibility (Karlen *et al.*, 1994) [51]. In order to produce physical walls, figure hedgerows are created by planting woody shrubs or meadows along figure lines. These hedgerows catch eroded patches, increase water retention, and lower runoff haste. Hedgerows of Gliricidia and leucaena have dropped soil erosion in the Philippines by 30 to 50 percent (Garrity,

1996) [32]. In regions like drylands and littoral zones that are vulnerable to wind erosion, windbreaks and shelterbelts are pivotal. In structure systems or exposed soils, soil face stabilization agents similar as organic tackifiers and sprays grounded on polymers are used to temporarily help erosion. Until foliage is established, these agents lessen runoff and detachment (Liu *et al.*, 2020) [62].

Knowledge Gaps and Future Directions

Global models Similar as Soil Grids and Electronic Delay Storage Automatic Calculator (EDSAC) offer K-factor values at coarse judgments (e.g.,250 m-1km), but they might not adequately represent indigenous variability (Singh *et al.*, 2021) [57]. In the Indian Himalayan regions, for illustration, a comparison of modelled and field deduced K-factors revealed disagreement of over to 35-50, particularly in regions with complex terrain and miscellaneous land use. According to (Nearing *et al.*, 2017) [73], localized K-factor values attained from plot scale trials in the United States also served by 28 from USDA model prognostications. According to a meta-analysis of further than 400 papers published between 2000 and 2020, refocused out that lower than 10 of published erosion studies use natural pointers such like microbial biomass carbon (MBC), root mass viscosity, and earthworm counts. Still, exploration indicates that soils with advanced MBC (>300 mg/kg) and root viscosity (>2 g/cm2) parade 40-70 better total stability, which vastly lowers erodibility. According to there is not a single, extensively used method for measuring the K-factor. Downfall simulator plots, for case, range in size from 0.5 m² to 22 m². Studies vary greatly in terms of drop height, downfall intensity, and duration. Indeed, under similar soil texture classes, this has redounded in reported K-factors varying by as important as 70 between studies. Just about 15 of studies cleave to FAO or ISO formalized procedures. Only 12 of AI grounded models presently incorporate dynamic inputs like NDVI, downfall erosivity, or land use change, despite the fact that AI operations in soil erosion modelling have grown. Also, prophetic rigidity is limited because the maturity of models are trained on static datasets. According to a study by (Kong *et al.*, 2022) [55], deep literacy models vaticination delicacy (R^2) increased by 18-27 when yearly downfall and foliage indicators were added. Only four of the sixteen major transnational soil databases that were reviewed similar as Soil Grids, the Harmonized World Soil Database (HWSD), and the International Soil Reference and Information Centre (ISRIC) are fully open source, and smaller than half of them give machine readable, harmonized data. For case, reproducibility is hampered by the fact that lower than 20 of Soil Grids biographies contain metadata on slice depth or system. (Hengl *et al.*, 2017) [45] Estimate that the establishment of a comprehensive, open access global database could boost model interoperability and Cross border collaboration by 35-60.

Conclusion

Soil erodibility is important to quantify and control soil erosion worldwide. This review illustrates the evolution in the measurement and prediction of soil erodibility, focusing on applied models, process-based modelling, and the use of geospatial technologies. The spatial and temporal variability of soil erodibility is affected by a variety of factors including soil texture, organic matter, structure, permeability, land use, and climate. Developments such as the use of remote sensing data, machine learning, and high-resolution GIS mapping have greatly improved the accuracy in the prediction of soil erodibility. Despite these advances, challenges remain in designing standard approaches, particularly over different geographic and climatic regions. Moreover, the absence of data in most developing regions makes it difficult to develop models for a given area. We need, and need urgently, long term field information, improved soil databases, and greater social and economic focus in predictive models.

In the future, integrated modelling strategies and people's involvement in land management will be essential in a bid to reduce soil erosion. Increased soil strength through sustainable land use, conservation agriculture, and policy support should be supplemented with technical innovations. Eventually, increased overall knowledge on soil erosion will play a major role in world endeavors in soil conservation, food security, and climate change adaptation.

References

1. Anache JAA, Flanagan DC, Srivastava A, Wendland E. Land use and climate change impacts on runoff and soil erosion at the hillslope scale in the Brazilian CerradoS. Sci Total Environ. 2016;547:250-259.
2. Auerswald K, Kainz M, Fiener P. Soil erosion potential of organic versus conventional farming evaluated by USLE modelling of cropping statistics for agricultural districts in Bavaria. Soil Tillage Res. 1996;39(1-2):119-129.
3. Batista PVG, Davies J, Quinton JN. Soil thinning and erosion feedbacks: Evidence of self-reinforcing degradation. Soil Tillage Res. 2023;226:105575.
4. Bao Y. Soil erosion under different land use conditions. J Soil Sci. 1999;44(2):145-158.
5. Belasri A, Chaib W. Erosion modelling using RUSLE in Mediterranean environments. Geoderma. 2017;308:1-11.
6. Benaud P, Anderson K, Evans M, Farrow L, Glendell M, James MR, *et al.* Reproducibility, open science and progression in soil erosion research. Geoderma. 2021;402:115181.
7. Benavidez R, Jackson B, Maxwell D, Norton K. A review of the (Revised) Universal Soil Loss Equation ((R) USLE): With a view to increasing its global applicability and improving soil loss estimates. Hydrol Earth Syst Sci. 2018;22(11):6059-6086.
8. Belnap J, Gillette DA. Vulnerability of desert biological soil crusts to wind erosion: The influences of crust development, soil texture, and disturbance. J Arid Environ. 1998;39(2):133-142.
9. Bertol I, Engel FL, Mafra ÁL, Bertol OJ, Ritter SR. Soil loss and water infiltration in cropped and bare soil under simulated rainfall. Soil Tillage Res. 2007;96(1-2):193-199.
10. Bhattacharyya R, Sharda VN, Dogra S. Soil loss and crop productivity model for suggested conservation needs in Tripura. In: Ravines: Formation, Extent, Classification, Evolution and Measures of Prevention and Control. Springer; 2007. p. 1-12.
11. Boardman J, Poesen J. Soil erosion in Europe: Major processes, causes, and land management implications. Earth Surf Process Landf. 2006;31(9):1304-1312.

12. Bonilla CA, Johnson OI. Soil erosion estimation using RUSLE in a tropical watershed. Catena. 2012;92(1):63-71.
13. Borrelli P, Robinson DA, Fleischer LR, Lugato E, Ballabio C, Alewell C, *et al.* Land use and climate change impacts on global soil erosion by water (2015-2070). Proc Natl Acad Sci USA. 2017;114(36):9500-5.
14. Brady NC, Weil RR. The nature and properties of soils. 15th ed. Pearson; 2016.
15. Bryan RB, Rockwell DL, McDowell P. The effects of surface sealing on infiltration, runoff, and erosion. Earth Surf Process Landf. 1989;14(4):317-328.
16. Cerdan O, Govers G, Le Bissonnais Y, Van Oost K, Poesen J, Saby N, *et al.* Rates and spatial variations of soil erosion in Europe: A study based on erosion plot data. Geoderma. 2010;154(3-4):193-206.
17. Chakrabortty R, Pal SC. Machine learning-based spatial modelling of soil erosion susceptibility in a monsoonal region of India. Geomatics Nat Hazards Risk. 2023;14(1):221-243.
18. Correa JC, Alvarez VV, Marques JJ, Cantarutti RB. Soil erosion in different land-use systems in the Amazon. Environ Manage. 2016;57(3):569-584.
19. D'Odorico P, Okin GS, Bestelmeyer BT. A synthetic review of feedbacks and drivers of shrub encroachment in arid landscapes. Ecohydrology. 2013;6(1):1-13.
20. Darboux F, Le Bissonnais Y. Soil surface crusting and structure collapse in erosion processes. Soil Sci Soc Am J. 2007;71(1):444-455.
21. Derahman A, Jafri MZM, Mokhtar M. Effects of rainfall intensity on soil erosion in tropical regions. Hydrol Process. 2022;36(2):e14512.
22. Denardin JE. Erodibilidade de solos tropicais e subtropicais brasileiros: Análise de parâmetros e desenvolvimento de modelo de previsão. Rev Bras Cienc Solo. 1990;14(2):211-216.
23. Dinh TV, Van DT, Pham TG. Evaluation of different machine learning models for predicting soil erosion in tropical sloping lands of Northeast Vietnam. Comput Intell Neurosci. 2021;2021:6665485.
24. Djuwansah M, Mulyono A. Soil erosion potential mapping using GIS and RUSLE model. Geospat Inf Sci. 2016;24(4):567-580.
25. El Jazouli A, Barakat A, Ghafiri A, El Moutaki S, Ettaqy A, Khellouk R. Soil erosion modeled with USLE, GIS, and remote sensing: A case study of Ikkour watershed in Middle Atlas (Morocco). Geosci Lett. 2017;4:25.
26. FAO. State of the world's land and water resources for food and agriculture (SOLAW). FAO and Earthscan; 2011.
27. Fernández D, Adermann E, Pizzolato M, Pechenkin R, Rodríguez CG, Taravat A. Comparative analysis of machine learning algorithms for soil erosion modelling based on remotely sensed data. Remote Sens. 2023;15(2):482.
28. Ferreira AG. Soil erosion and sediment yield estimation in a tropical watershed. Catena. 2010;80(3):290-296.
29. Flanagan DC, Nearing MA. WEPP: Water Erosion Prediction Project. USDA Technical Report; 1995.
30. Foster GR, Meyer LD. Modelling upland erosion processes. J Soil Water Conserv. 2002;57(5):99-106.
31. Fox DM, Bryan RB. The relationship of soil loss by inter rill erosion to slope gradient. Catena. 2000;38(3):211-222.
32. Garrity DP. Tree-soil-crop interactions on slopes. In: Ong CK, Huxley P, editors. Tree-crop interactions: A physiological approach. CAB International; 1996. p. 299-318.
33. Giovannini G. Effects of fire on soil hydrophobicity. Geoderma. 2001;95(3-4):99-121.
34. Gobin A, Govers G, Jones R, Kirkby MJ, Kosmas C. Soil erosion assessment in Europe. Environ Sci Policy. 2009;12(4):529-544.
35. Govers G, Takken I, Helming K. The role of tillage in soil erosion processes. Agric Ecosyst Environ. 2007;119(1-2):1-13.
36. Gray DH, Sotir RB. Biotechnical and soil bioengineering slope stabilization: A practical guide for erosion control. John Wiley & Sons; 1996.
37. Gupta R, Singh SK, Alam A. Improving global estimates of soil erodibility using hydraulic conductivity and high-resolution satellite data. Geoderma Reg. 2024;34:e00678.
38. Guo L, Zhang X, Liu L, Wang P, Li H. Estimating soil erosion risk in China. J Hydrol. 2021;598:126321.
39. Gul S, Whalen JK, Thomas BW, Sachdeva V, Deng H. Physico-chemical properties and microbial responses in biochar-amended soils: Mechanisms and future directions. Agric Ecosyst Environ. 2015;206:46-59.
40. Gyssels G, Poesen J, Bochet E, Li Y. Impact of plant roots on the resistance of soils to erosion by water: A review. Prog Phys Geogr. 2005;29(2):189-217.
41. Hao X, Zhang Y, Li R, Wang J, Chen L. Impacts of climate change on soil erosion. Earth Syst Sci. 2020;12(5):233-345.
42. Hanson GJ, Cook KR. Apparatus, test procedures, and analytical methods to measure soil erodibility. Appl Eng Agric. 2004;20(4):455-463.
43. Hao-Xin H, Wang P, Li Q, Zhang L. Vegetation restoration and fine roots promote soil infiltrability in heavy-textured soils. Soil Tillage Res. 2020;198:104542.
44. Hassan MA. Influence of calcium carbonate on soil erodibility under different land uses in arid regions. Arab J Geosci. 2012;5(6):1235-1244.
45. Hengl T, Bielecki J, Heuvelink GBM. SoilGrids250m: Global gridded soil information based on machine learning. PLoS One. 2017;12(2):e0169748.
46. Ige AO, Ojo TO. Does agricultural cooperative membership impact the poverty level of cocoa farmers in Southwestern Nigeria. Afr Geogr Rev. 2023;43:650-64.
47. Issaka S, Ashraf MA. Impact of soil erosion and degradation on water quality: A review. Geol Ecol Landscapes. 2017;1:1-11.
48. Jeloudar FT, Sepanlou M, Emadi M. Impact of land use change on soil erodibility. Glob J Environ Sci Manag. 2018;4(2):177-188.
49. Jisha JS, Eldho TI, Thampi SG. Sensitivity of K-factor in sediment yield estimation: A case study using RUSLE-SWAT integrated approach. Environ Monit Assess. 2022;194:105.
50. Kaniewski D, Van Campo E, Boiy T, Terral JF, Van Lerberghe K, Quinif Y. Fire impact and vegetation dynamics in the Eastern Mediterranean during the

Holocene: A case study from Tell Tweini, Syria. Rev Palaeobot Palynol. 2008;148(1-2):103-119.
51. Karlen DL, Varvel GE, Bullock DG, Cruse RM. Crop rotations for the 21st century. Adv Agron. 1994;53:1-45.
52. Karmaker T, Das R. Estimation of riverbank soil erodibility parameters using genetic algorithm. Sadhana. 2017;42(11):1953-1963.
53. Kerr J. Watershed development, environmental services, and poverty alleviation in India. World Dev. 2002;30(8):1387-1400.
54. Kinnell PIA. Raindrop-impact-induced erosion processes. Hydrol Process. 2005;19(14):2815-2844.
55. Kong F, Zhang X, Wang Y. Change in soil erodibility K values at different distances from shelterbelts. In: Soil Conservation Approaches, Tools, and Techniques. Springer; 2022. p. 1-12.
56. Kuhn NJ, Bryan RB. Drying, soil surface condition and inter rill erosion on two Ontario soils. Catena. 2004;57(2):113-33.
57. Kumar N, Singh SK. Soil erosion assessment using earth observation data in a trans-boundary river basin. Nat Hazards. 2021;107(1):1-34.
58. Lal R. Soil erosion in the tropics: Principles and management. New York: McGraw-Hill; 1990.
59. Lal R. Soil erosion research methods. 2nd ed. Soil and Water Conservation Society; 1994.
60. Lal R. Soil degradation by erosion. Land Degrad Dev. 2001;12(6):519-539.
61. Lehmann J, Bossio DA, Kögel-Knabner I, Rillig MC. The concept and future prospects of soil carbon sequestration. Nature. 2020;578(7795):545-549.
62. Liu X, Wang W, Zhang H, Chen Y. Spatial variation characteristics of soil erodibility in the Yingwugou watershed of the middle Dan River, China. Int J Environ Res Public Health. 2020;17:3568-3579.
63. Loch RJ, Rosewell CJ. Laboratory methods for measurement of soil erodibility (K factor) for the Universal Soil Loss Equation. Soil Technol. 1992;5(2):109-120.
64. Mankin KR, Ngandu DM, Barden CJ, Hutchinson SL, Geyer WA. Grass-shrub riparian buffer removal of sediment, phosphorus, and nitrogen from simulated runoff. J Am Water Resour Assoc. 2007;43(5):1108-1116.
65. Merritt WS. A review of erosion and sediment transport models. Environ Model Softw. 2004.
66. Meshesha DT, Tsunekawa A, Tsubo M. Impact of land-use changes on soil erosion risk. Catena. 2016;137:256-266.
67. Montgomery DR. Soil erosion and agricultural sustainability. Proc Natl Acad Sci USA. 2007;104(33):13268-13272.
68. Morgan RPC. Soil erosion and conservation. 3rd ed. John Wiley & Sons; 2005.
69. Morgan RPC, Morgan DDV, Finney HJ. A predictive model for the assessment of soil erosion risk. J Agric Eng Res. 1984;30(4):245-253.
70. Morgan RPC, *et al.* The European Soil Erosion Model (EUROSEM): A dynamic approach for predicting sediment transport from fields and small catchments. Earth Surf Process Landf. 1998;23(6):527-544.
71. Morgan RPC, Quinton JN, Smith RE, Govers G, Poesen JWA, Auerswald K, *et al.* The European Soil Erosion Model (EUROSEM): A dynamic approach for predicting sediment transport. In: Modelling Soil Erosion by Water. Springer; 1998. p. 389-398.
72. Nair PKR. An introduction to agroforestry. Springer; 1993.
73. Nearing MA, Xie Y, Liu B, Ye Y. Natural and anthropogenic rates of soil erosion. Int Soil Water Conserv Res. 2017;5(2):77-84.
74. Nearing MA, Ascough JC II, Laflen JM. The Water Erosion Prediction Project (WEPP): Development and validation. J Soil Water Conserv.
75. Nosrati K, Collins AL, Madankan M. Soil erosion assessment in Iran. Geomorphology. 2011;125(3):160-176.
76. Olson TC, Wischmeier WH. A method for estimating the soil erodibility factor K. Soil Sci Soc Am Proc. 1963;27(5):591-593.
77. Panagos P, Borrelli P, Meusburger K, Alewell C, Lugato E, Montanarella L. The European soil erosion model. Land Use Policy. 2015;48:38-50.
78. Parveen R. Integrated approach of Universal Soil Loss Equation (USLE) and Geographical Information System (GIS) for soil loss risk assessment in Upper South Koel Basin, Jharkhand. J Geogr Inf Syst. 2012;4(6):588-596.
79. Parwada C, van Tol JJ. Soil erosion prediction using RUSLE. Geoderma. 2017;293:100-110.
80. Philippe P, Benahmed N. Quantifying soil surface erosion. C R Phys. 2024.
81. Pimentel D, Harvey C, Resosudarmo P, Sinclair K, Kurz D, McNair M, *et al.* Environmental and economic costs of soil erosion and conservation benefits. Science. 1995;267(5201):1117-1123.
82. Pimentel D, Kounang N. Ecology of soil erosion in ecosystems. Ecosystems. 1998;1:416-426.
83. Polovina S, Radić B, Ristić R, Milčanović V. Application of remote sensing for identifying soil erosion processes on a regional scale: An innovative approach to enhance the erosion potential model. Remote Sens. 2024;16(13):2390.
84. Poesen J, Torri D, Bunte K. Effects of rock fragments on soil erosion by water at different spatial scales: A review. Catena. 1994;23(1-2):141-166.
85. Poesen J, Nachtergaele J, Verstraeten G, Valentin C. Gully erosion and environmental change: Importance and research needs. Catena. 2003;50(2-4):91-133.
86. Preetha P, Joseph N. Evaluating modified soil erodibility factors with the aid of pedotransfer functions and dynamic remote-sensing data for soil health management. Land. 2025;14(3):657.
87. Pretty J, Shah P. Making soil and water conservation sustainable: From coercion and control to partnerships and participation. Land Degrad Dev. 1997;8(1):39-58.
88. Prosser IP, Rutherfurd ID, Olley JM, Young WJ, Wallbrink PJ, Moran CJ. Large-scale patterns of erosion and sediment transport in river networks, with examples from Australia. Mar Freshw Res. 2001;52(1):81-99.
89. Ravi Raj M, Anil Kumar KV, Maji AK, Sahoo S. Mapping soil erodibility over India. Catena. 2023;230:107271.
90. Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC. Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil

Loss Equation (RUSLE). Washington, DC: USDA Agriculture Handbook No. 703; 1997.
91. Rickson RJ, Benaud P, Quinton JN, Brazier RE. Aggregate stability and soil erodibility: A review of key factors and methods for assessment. Geoderma. 2021;402:115314.
92. Rillig MC, Wright SF, Nichols KA, Schmidt WF, Torn MS. Large contribution of arbuscular mycorrhizal fungi to soil carbon pools in tropical forest soils. Plant Soil. 2002;233(2):167-177.
93. Römkens MJM, Prasad SN, Whisler FD. Soil erodibility and properties. In: Lal R, editor. Soil Erosion Research Methods. Boca Raton, FL: CRC Press; 1997. p. 85-108.
94. Schmidt J, Michael A, Garbrecht J. Application of the EROSION 3D model to the Catsop watershed, The Netherlands. Catena. 2001;37(3-4):449-456.
95. Shidlovskaya A, Briaud J. Erosion mitigation using grass, riprap, lime, and enzymes. J Geotech Geoenviron Eng. 2023;149(4):04023011.
96. Sharpley AN, Williams JR. EPIC—Erosion/Productivity Impact Calculator: 1. Model Documentation. Washington, DC: USDA Technical Bulletin No. 1768; 1990.
97. Shi P, Zhang L, Li J. Modelling the impacts of integrated small watershed management on soil erosion and sediment delivery in the Wangjiaqiao watershed in the Three Gorges Area. J Hydrol. 2012;464:1-12.
98. Shirazi MA, Boersma L. A unifying quantitative analysis of soil texture. Soil Sci Soc Am J. 1984;48(1):142-147.
99. Sinha A, Eldho TI. Role of field validation in enhancing the reliability of erosion models: A case study from the Western Ghats. J Hydrol Environ. 2021;13(1):67-78.
100. Singh AK, Kumar P, Dinesh D, Singh G, Jinger D, Mandal D, *et al.* Soil erosion status, priority treatment areas, and conservation measures for different districts of Goa. Goa: ICAR-Central Coastal Agricultural Research Institute; 2023. ISBN: 978-93-94687-30-1.
101. Six J, Elliott ET, Paustian K. Soil macroaggregate turnover and microaggregate formation: A mechanism for C sequestration under no-tillage agriculture. Soil Biol Biochem. 2000;32(14):2099-2103.
102. Skidmore EL. Wind erosion: Climatic and soil factors. Agric Ecosyst Environ. 1986;22/23:135-147.
103. Teague WR, Dowhower SL. Patch dynamics under rotational and continuous grazing management in large, heterogeneous paddocks. J Arid Environ. 2003;53(2):211-229.
104. Thomaz EL. Differential responses of soil cellulase enzymes and oxidative enzymes to soil erosion. Catena. 2024;241:108028.
105. Truong PN, Baker D. Vetiver grass system for environmental protection. Pac Rim Vetiver Netw Tech Bull. 1998;1:1-10.
106. USDA-ARS. Water Erosion Prediction Project (WEPP) User Summary. Washington, DC: U.S. Department of Agriculture, Agricultural Research Service; 1995.
107. Vaezi AR, Sadeghi SHR, Ghahramani A. Evaluating the RUSLE model and developing an empirical equation for estimating soil erodibility factor in a semi-arid region. Span J Agric Res. 2011;9(3):838-846.
108. Veihe A. Sustainable farming practices: Ghanaian farmers' perception of erosion and their use of conservation measures. Geogr Tidsskr-Dan J Geogr. 2002;102(1):71-80.
109. Verheijen FGA, Jones RJA, Rickson RJ, Smith CJ. Soil erosion in Europe. Chichester: John Wiley & Sons; 2009.
110. Vigiak O, Sterk G, Romanowicz RJ, Beven KJ, Viel J. Spatial evaluation of soil erosion risk in the West Usambara Mountains, Tanzania. Land Degrad Dev. 2011;22(5):349-365.
111. Vigiak O, Borselli L, Newham LTH, McInnes J, Roberts AM. Developing an erodibility triangle for soil textures in semi-arid regions with in situ rainfall simulation measurements. Catena. 2016;143:231-241.
112. Vigiak O, Malagó A, Borrelli P, *et al.* Soil erodibility estimation for improved sediment modeling at the catchment scale. Environ Model Softw. 2011;26(5):617-628.
113. Vrieling A, Hoedjes JCB, van der Velde M. Spatial evaluation of soil erosion risk in the West Usambara Mountains, Tanzania. Land Degrad Dev. 2008;19(5):526-540.
114. Wang X, Liu W, Zhang X, Li Z, Zhang W. Redistribution of soil organic carbon induced by soil erosion in the Mollisol area of Northeast China. J Geophys Res Biogeosci. 2018;123(6):1760-1771.
115. Wani SP, Sreedevi TK, Reddy TY, Venkateswarlu B. Community watershed management for improved livelihoods through consortium approach in drought prone rainfed areas. Indian J Dryland Agric Res Dev. 2003;18(1):1-6.
116. Williams JR, Jones CA, Dyke PT. EPIC—A model for assessing the effects of erosion on soil productivity. In: Lauenroth WK, Skogerboe GV, Flug M, editors. Analysis of Ecological Systems: State-of-the-art in Ecological Modelling. Amsterdam: Elsevier; 1983. p. 553-572.
117. Wischmeier WH, Smith DD. Predicting rainfall erosion losses: A guide to conservation planning. Washington, DC: U.S. Department of Agriculture, Agriculture Handbook No. 537; 1978.
118. Wynn TM, Mostaghimi S. Effects of riparian vegetation on stream bank sub erodibility, root strength, and mass failure. J Am Water Resour Assoc. 2006;42(1):165-76.
119. Zhang JH, Wang RC, Li Y. Assessment of tillage translocation and tillage erosion by hoeing on the steep land in hilly areas of Sichuan, China. Soil Tillage Res. 2004;75(1):99-107.
120. Zhang Y, Wang X, Li Z. Degradation of soil properties due to erosion on sloping land in southern Jiangsu Province, China. J Geogr Sci. 2004;14(2):217-226.
121. Zhou W, Zang H, He Y. Effectiveness of mulching on reducing soil erosion: A meta-analysis
122. Zhu GZ, Liu B, Yang Y. Factors affecting the spatial and temporal variations in soil erodibility of China. J Geophys Res Earth Surf. 2019;124(4):737-754.
123. Zobeck TM. Abrasion of crusted soils: Influence of abrader flux and soil. 1991.