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Comprehensive assessment of soil erosion using cloud-based geospatial analysis: Insights from the RUSLE model

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Abstract

The erosion of soil remains a major environmental threat as it results in land degradation, low agricultural productivity, and the destabilization of ecosystems. Analyzing its spatial distribution is vital for better land management and designing effective practices. This research deploys a cloud-based geospatial infrastructure to estimate soil erosion using the Revised Universal Soil Loss Equation (RUSLE). The rainfall erosivity factor (R) is generated from Climate Hazards Group Infrared Precipitation with Station (CHIRPS) annual precipitation data, and the soil erodibility factor (K) uses soil texture classification estimates from the USDA's Open Land Map. The LS factor accounts for the topographic effects of erosion intensity using Digital Elevation Models (DEMs). Changes in vegetation cover, evaluated by the Sentinel-2 derived NDVI, inform the cover management factor (C) while land use, along with slope data, define the conservation practice factor (P). The combined study provides a detailed soil loss map of the Potwar region, revealing that approximately 8.10% of the total area (17,778 km²) suffers from severe erosion, contributing the highest average soil loss rate of 46.74 t/ha/year. Additionally, 67% of the area is moderately eroded, while only 11.13% experiences slight erosion. The most sensitive regions, approximately 17,778 km² (8.10% of total area), suffer the highest average soil loss of 46.74 t/ha/year. The results of Cloud computing technology applied to geospatial analysis for soil erosion issues show its effectiveness in facilitating remediation efforts while also enabling the assessment of multifaceted environmental systems.

Keywords: RUSLE; GEE; chirps; NDVI; soil loss; Potwar; Pakistan

Introduction

Soil erosion is a major environmental process that causes land degradation, decreases agricultural productivity, and threatens ecosystem stability. In Pakistan, the Potwar Plateau is one of the most erosion-prone regions due to its semi-arid climate, rugged topography, and intensive agricultural practices. Globally, over 75 billion tons of fertile soils are lost annually due to erosion by water and wind (Abdelrahman *et al*., 2016; Arabameri *et al*., 2019), severely impacting food security, water quality, and biodiversity. While the United States reports moderate soil loss (~16 t ha^{-1} $year^{-1}$).Regions across South America, Sub-Saharan Africa, and South Asia frequently experience losses exceeding 30–40 t/ha/year (https://openknowledge.fao.org/). In Europe, water-induced erosion is the most widespread type, responsible for over 130 million hectares of degraded land (Panagos *et al*., 2015). Such trends highlight the urgent need for spatially detailed, scalable erosion monitoring methods.

Recent studies have shown that soil processes, including its movement and accumulation, are deeply modified by nutrients and carbon. The carbon content of the soil that has been eroded will lead to a 75-85% reduction in carbon concentration, resulting in the release of carbon into the environment(Ali, 2011; Barakat *et al*., 2023). An in-depth study was done in the Patiala-Ki-Rao watershed to achieve optimal sustainable land management post-erosion while focusing on its landform and physicochemical features. Water management is critical for achieving goals that depend on understanding the geography and the soil's physicochemical properties. (Ali *et al*., 2022). For effective soil erosion estimation, there is a need to combine various models and assessment tools, as well as climatic factors such as soil texture, flora, and even anthropogenic activity. Modeling and monitoring soil erosion is important in agriculture, and Digital Elevation Models can be obtained through optical and radar remote sensing. The use of multi-

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temporal satellite images to monitor seasonal land use variability can improve accuracy (Basharat *et al*., 2022).

Traditional models like the Universal Soil Loss Equation (USLE) are widely used but often lack precision in diverse topographies or large-scale studies (Kebede *et al*., 2021; Koirala *et al*., 2019; Panagos *et al*., 2021). To address these limitations, the Revised Universal Soil Loss Equation (RUSLE) incorporates topographic, climatic, soil, and land-use parameters (Kayet *et al*., 2018; Alewell *et al*., 2019). However, applying RUSLE at large scales is computationally intensive, especially in data-scarce regions like Potwar. In Pakistan, the Potwar Plateau is highly susceptible to erosion due to steep topography, sparse vegetation, and intense monsoonal rainfall. To address this, the RUSLE incorporates multiple environmental factors: rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), land cover (C), and conservation practices (P), providing more reliable estimates (Dutta *et al*., 2015;; Aslam *et al*., 2020; Meliho *et al*., 2020; Sandeep *et al*., 2021).

This study leverages Google Earth Engine (GEE), a cloud-based geospatial platform, to perform high-resolution RUSLE-based erosion assessment using open-access datasets and remote sensing (Nasir *et al*., 2023). The combination of GIS, RUSLE models, and remote sensing helps to evaluate the impacts of sedimentation on the storage capacity of the water system. Making use of the GEE capabilities is a useful tool for carrying out in-depth environmental investigations. In addition, this study aids the comprehension of the soil erosion processes by introducing erosion severity classification, which allows for the formulation of more effective context-sensitive land management policies (Madhukar *et al*., 2023).

In Pakistan, the Potwar Plateau is one of the most erosion-prone regions due to its semi-arid climate, rugged topography, and intensive agricultural practices. Although various studies have used the RUSLE model in different global regions, its integration with cloud-based platforms such as Google Earth Engine (GEE) remains limited in Pakistan, especially at regional scales. This study is among the first to implement a high-resolution, cloud-based RUSLE assessment using GEE for the entire Potwar region, providing unprecedented spatial detail and enabling real-time environmental analysis through remote sensing and open-access datasets. Unlike previous studies, we used a consistent, multi-source geospatial pipeline to derive R, K, LS, C, and P factors from CHIRPS, DEM, Sentinel-2 NDVI, MODIS, and OpenLandMap datasets. The integration ensures rapid, scalable, and transparent erosion modeling with regional specificity.

Moreover, the study introduces an erosion severity classification to identify priority zones for land management. By mapping and quantifying soil loss, this research supports context-sensitive conservation planning and offers policy-relevant insights. It also opens avenues for future integration with AI and machine learning to further automate and optimize erosion modeling in cloud environments. This will help to comprehend the practical implications and effectiveness of these actions in different environmental and geographical conditions. This work is an exercise in enhancing understanding of soil erosion problems and provides a new perspective on studying the problem of soil erosion through integrating the RUSLE Model with the GEE Platform. Its objectives are to classify the severity of soil erosion in the potwar region, measure the rate of sedimentation, and provide insightful information on soil erosion patterns. Additionally, provide actionable insights for land conservation in Potwar.

Material and Methods

Study area description

This study was undertaken within the bounding geography of the Potwar Plateau region, approximately 31,000 km², and includes four key districts: Rawalpindi, Jhelum, Chakwal, and Attock. The region's topography is primarily composed of shale and sandstone due to the significant contribution of natural forces like water and wind that shape the land for topsoil formation. The vegetation cover mainly consists of a semi-arid environment in the form of the scrub of arid deciduous trees. However, because the climatic extremes in the Potwar region are quite diverse, most of the agricultural producers in the area face complications as they attempt to achieve constant staple crop production because of the broad range of weather elements. The study area is positioned in a humid subtropical climate zone with a mean annual rainfall between 950 and 2000 mm (Li *et al*., 2023). Geographically bound by the Jhelum and Indus Rivers, the terrain is characterized by undulating hills, dissected gullies, and steep slopes composed mainly of shale and sandstone. The plateau lies in a semi-arid to sub-humid climate zone, with annual rainfall ranging from 950 to 2000 mm and temperature extremes from 4.7°C in winter to 38°C in summer. Dominant land uses include rainfed agriculture, rangeland, and dry forests, with growing pressures from urban expansion and overgrazing, both of which exacerbate soil degradation and runoff (Cheema & Bastiaanssen, 2012). The features that surround the study area comprise the Jhelum River, the Soan River, and the Haro Bowl, which mark the boundaries. Within this region, there are sandy and rocky landforms that significantly aid in the understanding of ecological processes in the study. Figure 1 depicts an

overview of the study area in the format of three distinct panels. Panel 1(a) depicts the location of Pakistan on the world map, which provides insight into the broader region of interest, 1(b) focuses on Punjab province and depicts population data using a thematic map, while 1(c) focuses on the study area and depicts it using a Digital Elevation Model DEM that shows the topography of the region as well as some of the expected level changes across the area.

Data Sources

This study integrated multi-source geospatial datasets accessible via the Google Earth Engine (GEE) platform to calculate the RUSLE parameters. This study leverages Google Earth Engine (GEE), a cloud-based geospatial platform, to perform high-resolution RUSLE-based erosion assessment using open-access datasets and remote sensing. For this purpose, we applied to the GEE for soil loss estimation in a geospatial way. Thematic layers in GEE are structured within a GIS environment based on prepared

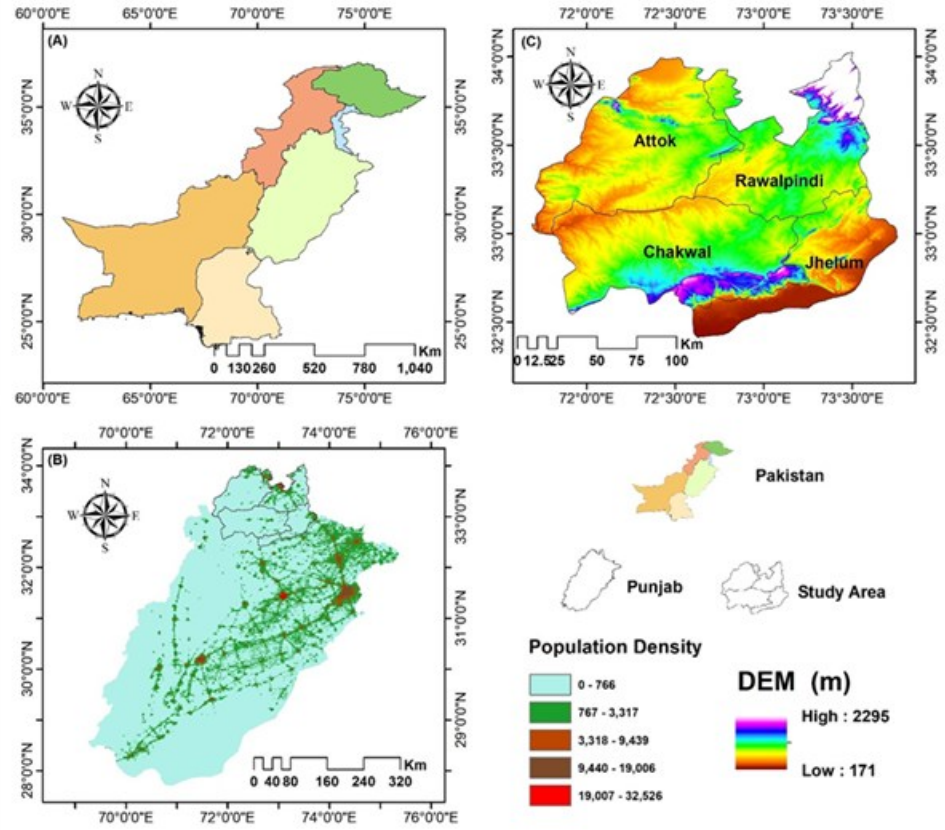


Figure 1: Study Area Map of the Potwar Plateau Region (a) Location of Pakistan on the World Map (b) Punjab Province with Population Density Representation (c) Detailed Study Area Highlighting Topographic Features with Digital Elevation Model (DEM)

Table 1: Datasets used in this research

Factor	Source	Resolution
R (Rainfall)	CHIRPS v2.0	0.05° (~5.5 km)
K (Erodibility)	OpenLandMap Soil Grids + USDA Texture	250 m
LS (Slope & Length)	SRTM DEM	30 m
C (Vegetation)	Sentinel-2 NDVI	10 m
P (Practices)	MODIS MCD12Q1 LULC + DEM	500 m (resampled to 30 m)

merged information from different origins. Land Use and Land Cover (LULC) data was extracted from MODIS MCD12Q1 (Type 1 classification) (500 m resolution) to define land use categories relevant to the C and P factors, and resampled to 30 m using bilinear interpolation. To ensure reliability, we validated MODIS LULC against Sentinel-2 composites and Google Earth high-resolution imagery. An accuracy assessment of 150 random points showed an overall accuracy of 85.6% and a Kappa coefficient of 0.81. All datasets were chosen for their availability, spatial consistency, and suitability for scalable erosion modeling within cloud environments. Table 1 illustrates the data types and sources used in this study.

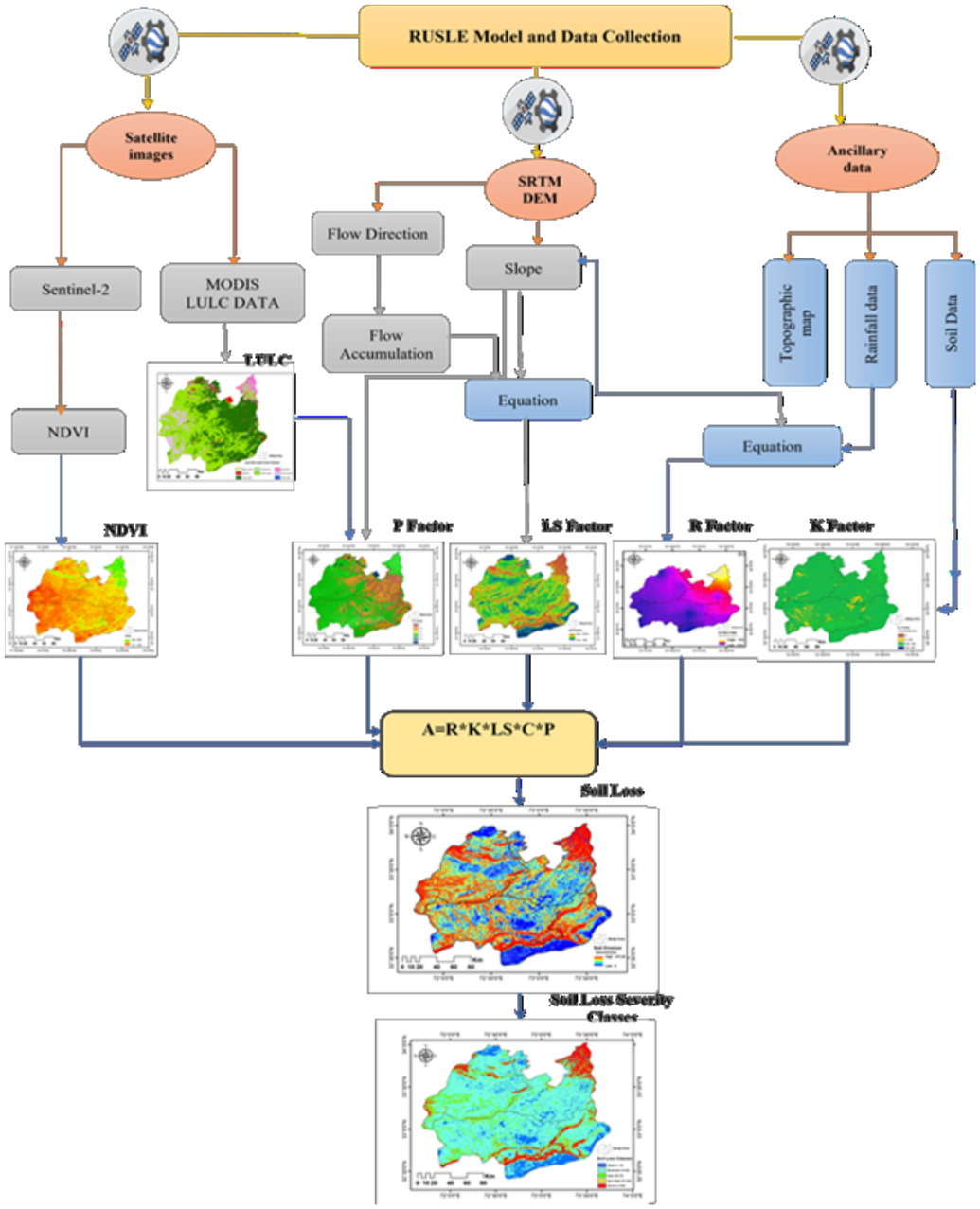


Figure 2: Methodological flowchart for the estimation of soil erosion using the GEE

RUSLE model

The Revised Universal Soil Loss Equation (RUSLE) was adopted in this study to evaluate the long-term soil erosion rates. RUSLE's methodology is enhanced with modern computational techniques by using physically significant input variables that can easily be sourced from existing databases, satellite imagery, or even digital elevation models (DEM). Switching from the global soil, the declining assessment that which RUSLE was initially created for and modifying it for the specific geology conditions in the Potwar region proved to be especially difficult. Most shockingly, this study ignored flow divergence and convergence in multi-faceted topographies, which would otherwise alter the local processes of soil erosion (Wang *et al*., 2022). To calculate the Average Annual Soil Loss (A) using RUSLE (Equation 1), it integrated imagery from the GEE satellite and the surrounding geographical datasets, writing a new method in Google Earth Engine (GEE). The evaluation included the main factors of RUSLE (Doulabian *et al*., 2021; Alitane *et al*., 2022).

$$A = R \times K \times LS \times C \times P \qquad 1$$

Equation (1) represents the product of variables R, K, LS, C, and P.

Where:

- **A** = Average annual soil loss (t/ha/year)
- **R** = Rainfall erosivity (MJ·mm/ha/h/year)
- **K** = Soil erodibility (t·ha·h/ha·MJ·mm)
- **LS** = Topographic factor (dimensionless)
- **C** = Cover management factor (dimensionless)
- **P** = Support/conservation practice factor (dimensionless)

The variable R represents the rate of rainwater erosion, measured in millimeters per hour per hectare. On the other hand, the value C in the given equation represents the dimensionless crop management factor. The symbol K refers to the soil erodibility factor that is calculated in metric kilos per hectare per megajoule per millimeter. One of the parameters of measurement is the slope length steepness factor, LS, which ranges from 0 to 1. The dimensionless variable P, which varies between 0 and 1, indicates the amount of support that can be given to land management. The retention of erosion in a defined area is influenced by a variety of factors like climate, land use, topography, and soil. The results provide a perspective toward the conservation of soil concerning land management and give more emphasis to soil erosion as a multifaceted phenomenon. The methodological workflow describing this approach is given in Figure 2.

Rainfall erosivity factor (R)

According to studies, GEE is useful for estimating rainfall erosivity, a geospatial analysis that determines a land's rainfall erosivity factor (R) and its inherent danger toward soil loss (Nam *et al*., 2014). Rainfall is one of the primary causes of soil erosion, especially during the period of heavy rain when particles get detached and carried away. A higher intensity of precipitation results in a great availability of larger raindrops, which leads to the already mentioned processes getting intensified – too much sediment gets carried away, which leads to an increase in rill and sheet erosion (Shen *et al*., 2016). The precipitation data was sourced from the CHIRPS dataset to assess the R factor. The analysis is based on a comparative study model (Sud *et al*., 2024) defined by Equation 2, which correlates annual precipitation (P, measured in millimeters) with the ratio of rainfall erosivity (R, expressed as MJ mm ha^{-1} h^{-1} y^{-1}) and expresses how much precipitation may negatively affect the soil by displacing it. To determine rainfall erosivity of interest, an erosivity map was created in ArcGIS 10.5, and the corresponding R factor was calculated based on precipitation. Annual rainfall estimates were obtained using a methodology commonly applied in international, multidisciplinary studies aimed at assessing the potential impact of rainfall on land degradation and supporting comprehensive conservation planning.

$$R = 79 + 0.363 \times P \qquad 2$$

Soil Erodibility (K) factor

As stated by Sud *et al*. (2024), the K factor is an important soil physical parameter as it determines the degree of erosion vulnerability, which defines the possibility of soil erosion in the land area in terms of soil displacement from rain and surface runoff. This factor is affected by the combination of multiple soil properties, such as its mineralogical and chemical, physical, and morphological components. K is the coefficient of soil at the loss of one unit for each unit of soil of soil erosion process at a bare eroded plot (Haseeb *et al*., 2024). The K factor is a significant measurement for the estimate of how easily the soil particles can be removed and transported by rainfall as well as runoff. In varying degrees, a soil's

texture, structure, organic matter content, and permeability affect this factor. With the RUSLE model, the Potwar region K factor was calculated through GEE and satellite images. The K factor for the Potwar region is calculated using GEE, which mostly depends on preexisting datasets and literature's soil type and textural maps (Sud *et al*., 2024). The analysis subdivided the subject matter region into four distinct types of soil; each ascribed a K Factor ranging from zero to one where a greater value implies a higher risk of erosion. Four dominant soil types were identified in the region using OpenLandMap texture classes. K-values were assigned using USDA nomographs and peer-reviewed sources (Haseeb *et al*., 2024; Zhang *et al*., 2024). Acknowledging regional variability, the uncertainty in K-factor assignment was reduced by:

- Cross-referencing soil texture with FAO digital soil maps.
- Compared with local soil sampling datasets (where available).
- Sensitivity analysis in ArcGIS for ±10% variation in K-factor.

GEE, as applied in this study on soil strip ability estimation at a regional scale, enhances the representation of soil erosion process accuracy. It enhances the precision of modeling erosion risk by taking into consideration spatial variability as well as local soil characteristics of the Potwar region.

Slope length steepness (LS) factor

Modeling soil erosion includes an LS factor, which considers the combined topographic effect on erosion by integrating slope length (L) and slope steepness (S) into one variable. The LS factor evaluates the amount of erosion that is increased or reduced due to the amalgamation of topography and slope length, which decides the expected soil erosion at any gradient to a standard reference incline that is set at 22.6 meters over a 9 percent gradient. The longitudinal and latitudinal component factors, LS, slope steepness, and length, are sufficient to measure the effect of terrain on erosion susceptibility at a given region and time (Marchetti *et al*., 2012). The height of the inclination (L) defines the degree to which the slope will contribute towards the soil being eroded. Slope length is the set horizontal gap between the point where the runoff water enters a channel, or deposition begins, and the point where overland flow commences. Increasing the inclination will increase soil erosion per unit area (Mary *et al*., 2023).

The impact of steepness on erosion is quantified by the slope steepness factor (S), which measures every specific portion of a soil slope. Steeper inclines tend to have a more notable effect on erosion than the length of the slope. Erosion of shallower slopes within 10% and 25% incline increases dramatically to a greater degree. The equation 3 is made up of LS, Qa, Sg, and M. The slope steepness factor is classified as LS, the flow accumulation grid is designated as Qa, the grid slope in percentage is Sg, and the grid area is M, y is in the range of 0.2 to 0.5. Consider how the slope's grade changes the value of m. For m values greater than 4.5, m should be set to 0.5. Increments from 3.5% to 4.5% require that m equals 0.4, while in increments from 1.0% to 3.0%, m should be set to 0.3. Furthermore, if the gradient exceeds 1%, m ought to equal 0.2.

$$LS = \frac{(\text{Flow accumulation} \times \text{CellSize}^{0.4})}{22.13} \times \frac{(\text{SinSlope})^{1.3}}{0.0896} \quad (3)$$

Where "Flow Accumulation" is the grid cell's total upslope supporting area, "LS Factor" is a pattern of length and steepness of slope. The 'Cell Size' factor offers the size of a single grid cell, while the 'Sin slope' is in sin, indicating the slope's degree.

Crop Cover (C) Factor

The cover factor (C) is influenced not only by land cover but also by anthropogenic activities, particularly in association with erosion control activities (Ozsahin *et al*., 2018). Consideration of land use activities implies that this factor is complicated due to its multifaceted character and continuously changing patterns. Satellite imagery with a spatial resolution of 10 meters was additionally acquired through GEE to derive NDVI (Jodhani *et al*., 2023). NDVI is defined as the most popular index of the greenness factor determined by the difference in reflection from near-infrared (NIR) and red spectral bands as expressed in Equation 4. As ranging in particular usefulness, it can serve as an indicator of vegetation cover about soil loss, from which most directly stems the C factor of the Universal Soil Loss Equation (USLE) (Almagro *et al*., 2019). The values of vegetation density or vegetation cover and distribution predicted by GEE are arguably most accurately termed NDVI and serve as the best predictor for soil erosion features, which are often underestimated.

$$NDVI = (NIR - Red)/(NIR + Red) \quad 4$$

Support practice (P) factor

The effectiveness of soil erosion management on the vegetative cover, soil biomass, and related runoff management efforts is evaluated in the P factor. The P factor is a component of the Revised Universal Soil Loss Equation,

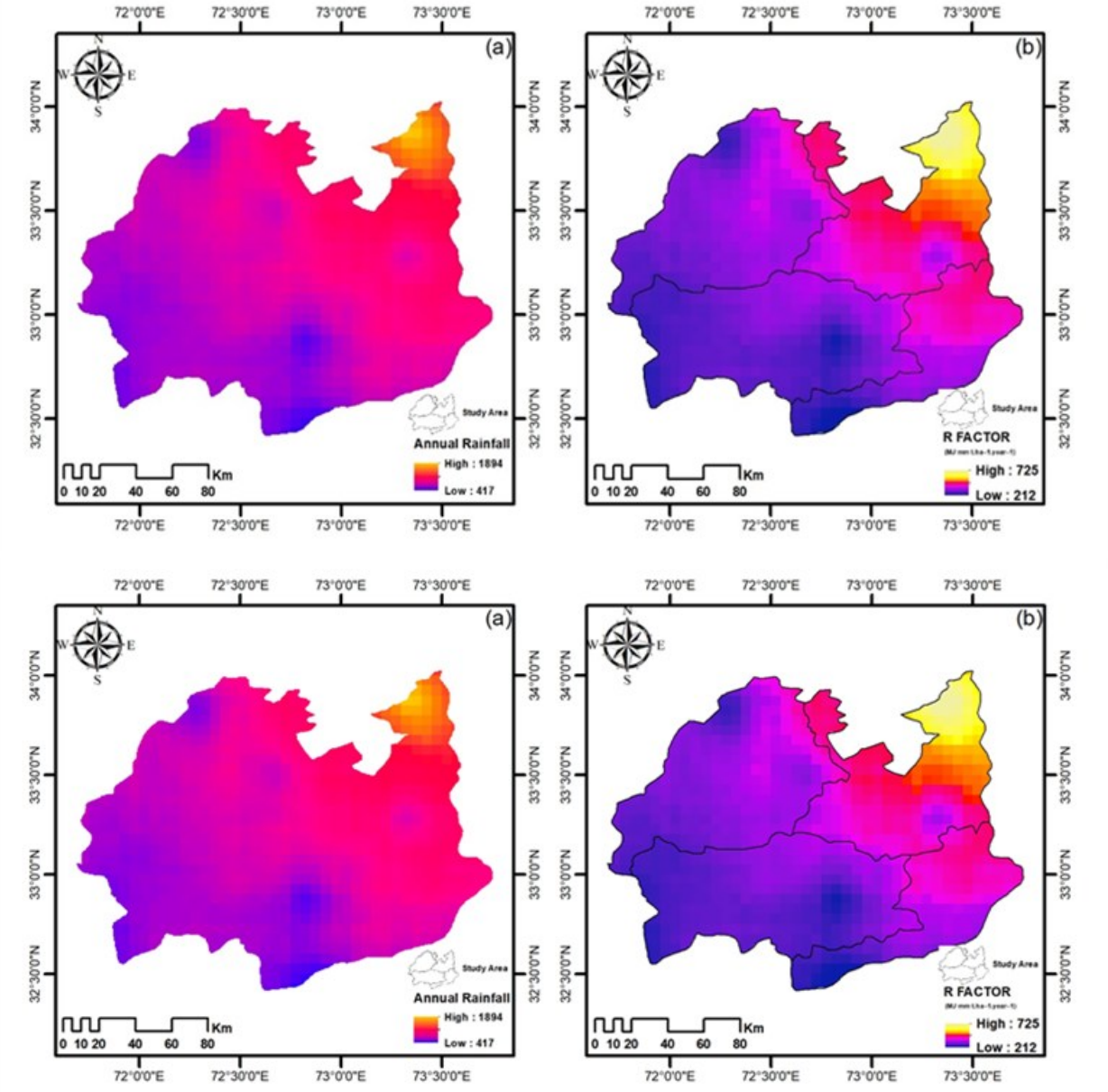


Figure 3: (a) Annual precipitation distribution from CHIRPS dataset (mm); (b) Rainfall erosivity (R factor) map of Potwar region (MJ mm ha^{-1} h^{-1} yr^{-1}). High R values indicate regions with greater potential rainfall-induced erosion

which considers the effects of the vegetation, conservation measures, and erodible land use practices and their intensities, length of the slope, and time on soil erosion. For improved efficiency and precision in this process, the GEE is applied to the remote sensing of the P factor (Maqsoom *et al*., 2020; Batool *et al*., 2021). This method facilitates the effectiveness of conservation strategies to be estimated more accurately, which combines spatial data on land management activities and improves the soil erosion estimation model accuracy. By using GEE, we aim to develop a function that permits the retrieval of relevant bands or features related to cover, structures like land cover, support practices, land use intensity, slope length, and certain other modifications. This function makes it possible to determine the P factor value. By adding image sets for every component set, the P-factor map is produced. The seamless integration of remote sensing and GEE's extensive geographic capabilities results in the rapid processing of vast amounts of geographic data, leading to comprehensive assessments of soil erosion trends and patterns at an unprecedented scale. P-values were based on slope classes and land use types, following the methodology from Ahmed *et al*. (2013). Slope classes were extracted from the SRTM DEM, and LULC was classified using MODIS. For instance,

- Cropland on <5% slope: P = 0.5
- Cropland on >15% slope: P = 0.8
- Urban/Forest areas: P = 1.0 (no conservation)

This slope–land use matrix method enabled spatially varying P-factor assignment in the GEE script, enhancing realism over uniform values. The aim is to apply this method through the GEE platform for effective decision-making in land management aimed at sustainable practices to minimize soil erosion. For estimating the mean annual rate of soil erosion in the Potwar region, the GEE was used. This method is described as a multiplication of the six factors of the RUSLE model. With the combination of geospatial data and the computational hardware provided through GEE, we made a detailed assessment of the soil erosion risks within the region.

Slope

The slope of the terrain plays a crucial role in calculating soil erosion and is an essential component of the RUSLE. Water runoff increases in steeper terrains due to gravity, thus acting with greater erosive power. The intensity of rainfall is heightened, and water is accelerated, resulting in loosening and transportation of soil particles. One of the components of RUSLE is the LS factor, which estimates the risk of erosion based on the length and steepness of the slope. The depiction and categorization of slope maps permit regions to be delineated according to their degree of slope and, therefore, help to indicate areas prone to soil erosion. Slope maps showing the combination of R factor, K factor, C factor, and P factor will permissively analyze the soil loss in those regions. To maintain effective preservation of land management within steep regions, having an idea about the slope is of utmost importance. This also aids in creating appropriate land use policies. The accuracy of slope computations, which is critical in modeling soil erosion, depends directly on the precision of elevation data and slope derivation methods (Alewell et al., 2019).

Results

The current work shifts the focus of soil erosion research in the Potwar region by integrating new approaches. It combines the Revised Universal Soil Loss Equation with the procedure of geographic information systems and remote sensing techniques. The approach enables the enhancement of RUSLE by considering soil loss at a very detailed, cell-by-cell basis within the study area boundary. More importantly, this analysis not only measures soil erosion and provides a mapping of the study area's unique risk zones but also delineates and quantifies soil erosion. Remote sensing and GIS provide an additional consideration of the numerous factors that drive the soil erosion processes using spatial data. Attributes such as topography, land cover, rainfall, and soil type, among others, are used to integrate and retrieve the needed factors for the RUSLE model. This combination of data captures the complicated and very sophisticated phenomena of soil erosion processes and makes the assessment more feasible. The maps derived from RUSLE parameters resulted from an elaborate analysis and processing of data, and these maps form the base for explaining and understanding soil erosion in the Potwar region. Analyzing these outputs systematically will provide insight into the intricacies concerning how soil erosion is distributed, its intensity, and the fragility of the designated research area.

Rainfall erosivity (R Factor)

The amount of rainfall plays an important part in the processes of soil erosion, and precipitation is an important factor in determining the sediment yield and rates of erosion in different seasons. Past studies indicate that the average annual precipitation is a good estimator of changes in soil erosion because it is easy to calculate, the data is of good quality, and it greatly depicts the patterns of a region (Seutloali *et al*., 2018; Qin *et al*., 2023). The CHIRPS dataset through GEE, which guarantees full spatial coverage. The R factor values derived from CHIRPS precipitation data showed a significant spatial gradient. Values ranged from 212 to 725 MJ mm ha^{-1} h^{-1} $year^{-1}$,

with a mean of 493 MJ mm ha^{-1} h^{-1} $year^{-1}$ and a standard deviation of 83. Higher R values were concentrated in the

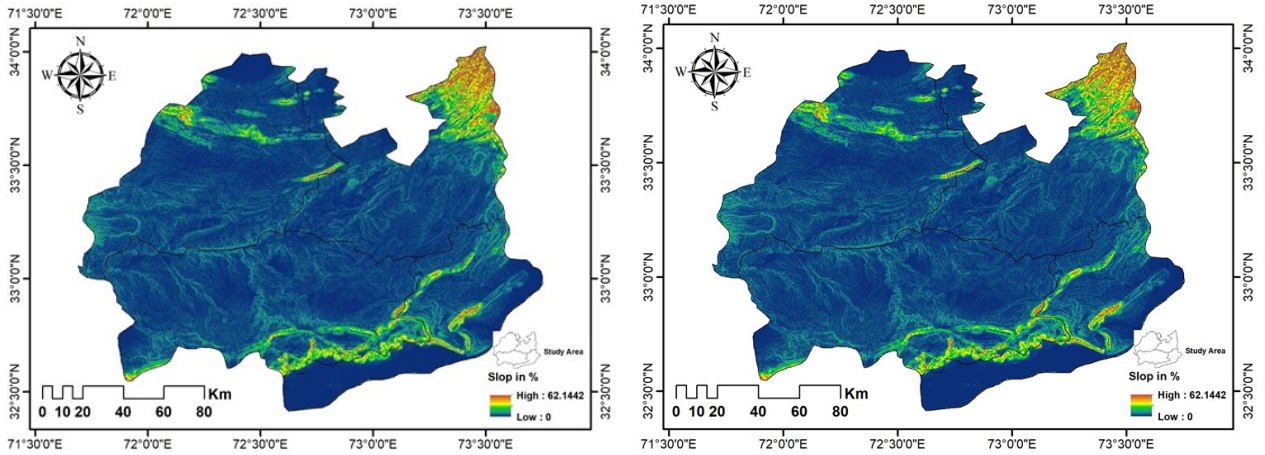


Figure 4: Slope map of the Potwar region derived from SRTM DEM

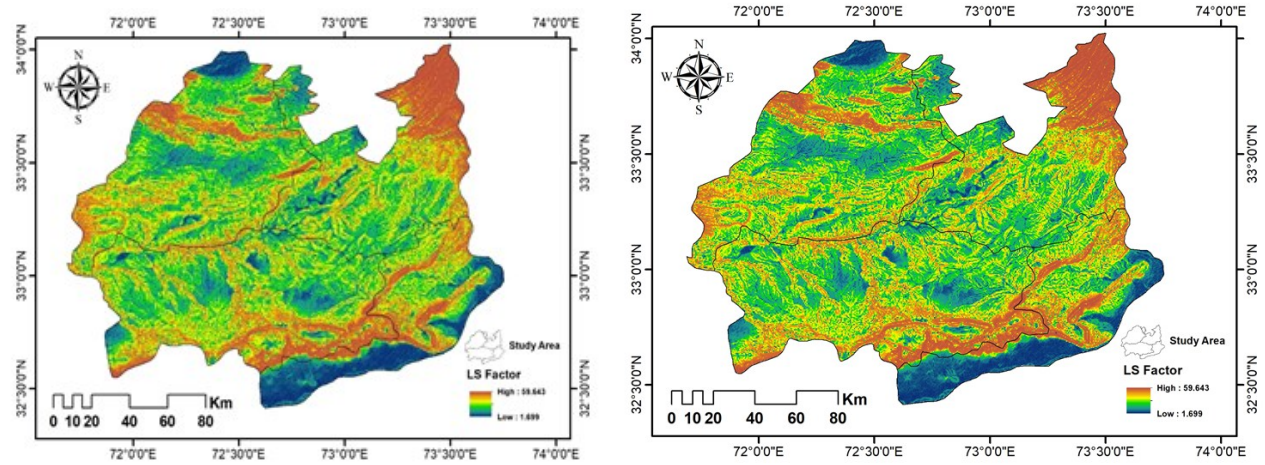


Figure 5: Topographic LS factor map of the Potwar region (dimensionless)

northwestern and central zones, indicating regions with more intense rainfall and higher potential for erosive storms (Figure 3b).

Figure 3(a) indicates the distribution of rainfall in the region to assist in understanding precipitation amounts within the region and their intensity. Meanwhile, Figure 3(b) shows corresponding R factors and reveals areas with high and low values of the factors, thus highlighting the range of the erosivity of the regions. This analysis gives a more detailed view of the potential of rainfall erosion and the impact it has on soil erosion processes. The combination of rainfall and the R factor facilitates essential erosion risk assessments, which is the first step in formulating and implementing effective strategies that prevent soil loss and promote sustainable land management.

LS factor

The LS factor is a critical component in measuring soil erosion using contours (Figure 4). It combines the L and S factors of slope to calculate the erosion rates. The LS factor can be determined by using Equation (3). Calculations indicate that there is variation in the potwar region, meaning that the region possesses diverse landforms. Areas with the most significant LS factors between 1.6 and 59 (with an average of 6.82 and a standard deviation of 7.95) are caused by steep slopes and elongated flow paths, which make them prone to soil loss. These exceptionally elevated values also suggest that the Rawalpindi

area is especially prone to erosion. The Rawalpindi and Chakwal districts exhibited elevated LS values due to steep terrain and longer slope lengths, making them more susceptible to surface runoff and rill erosion (Figure 5). The significant regional heterogeneity illustrates and underscores the persisting need for practical approaches in the soil management of the anthropogenic region. This, coupled with the varying factors on soil erosion across the watershed, means that soil conservation measures and land use policies must be engineered on a case-by-case basis.

Analysis of NDVI

Analyzing the NDVI of the Potwar region facilitates an augmentation to the understanding of vegetation composition within the region. Alongside managing vegetation conditions and density, NDVI also provides significant information regarding greenness within the area. Figure 6 presents the density and health of vegetation in the region, which is quantified with values between -0.28 and 0.60 (with a mean of 0.18 and a standard deviation of 0.08). Higher values are recorded when the region is densely populated with healthy vegetation, while lower values indicate sparsely populated, barren zones. Vegetational density is scattered across the watershed; it can be found in abundance in some regions as indicated by their high NDVI values and is relatively scarce in other regions due to the measured NDVI values tending closer to 0. In the context of the Potwar region, measuring NDVI quantitatively facilitates land use and sustainable conservation planning within the area. The case study presented here demonstrates how analyzing geographic and

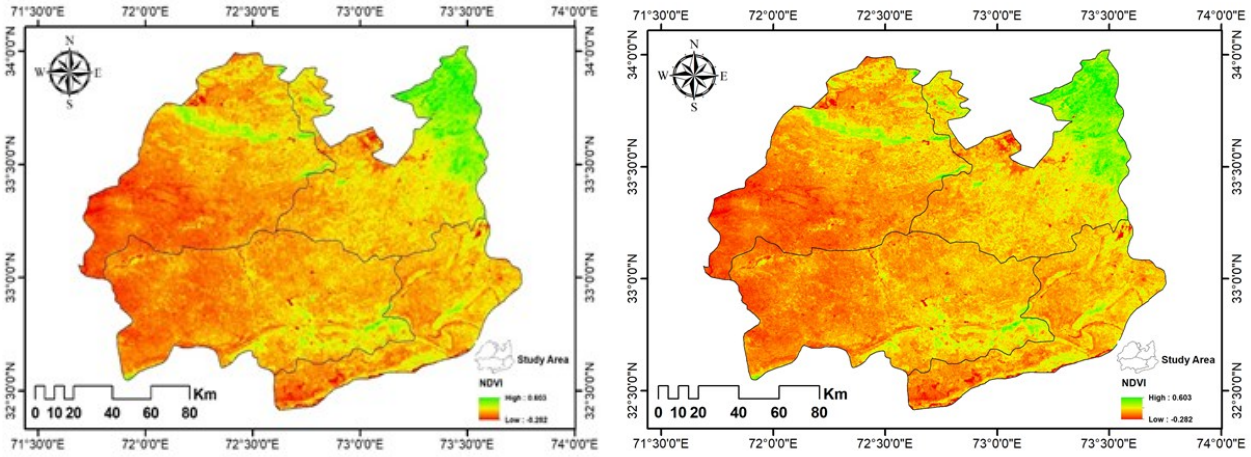


Figure 6: NDVI map for Potwar region

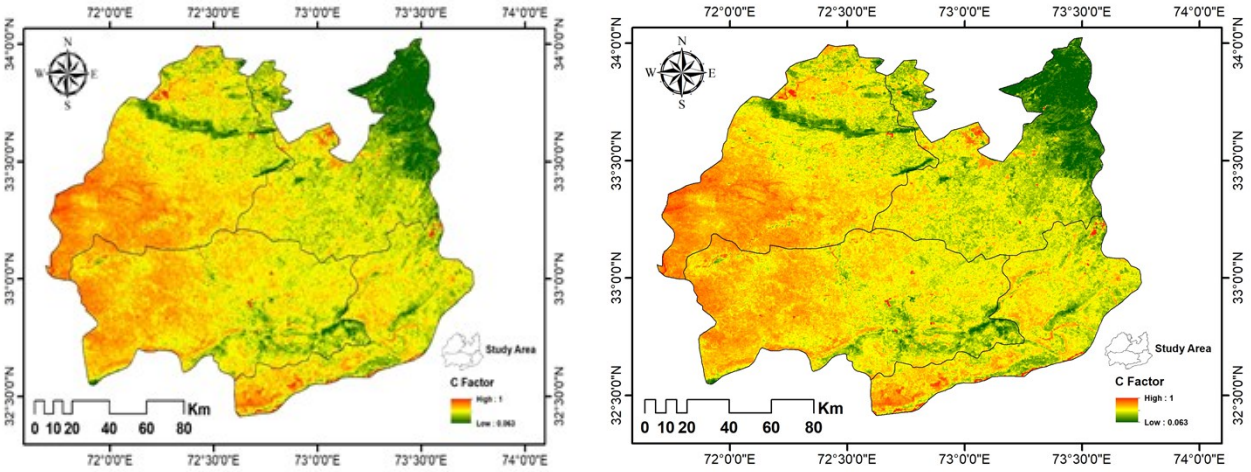


Figure 7: Cover Management Factor (C factor) map for the Potwar region (dimensionless), derived from NDVI

vegetation aspects can help in making well-informed decisions. Stakeholders who take part in this study can appreciate the comprehension that the NDVI study provides and act accordingly by promoting ecological sustainability as well as ensuring that further development is carried out sustainably throughout the region.

the study area, crucial for prioritizing conservation zones (Figure 7). This range makes it possible to develop targeted soil conservation measures that determine the effectiveness of erosion control techniques. Ultimately, focusing soil conservation measures on areas with a greater likelihood of being eroded facilitates greater long-term ecological health.

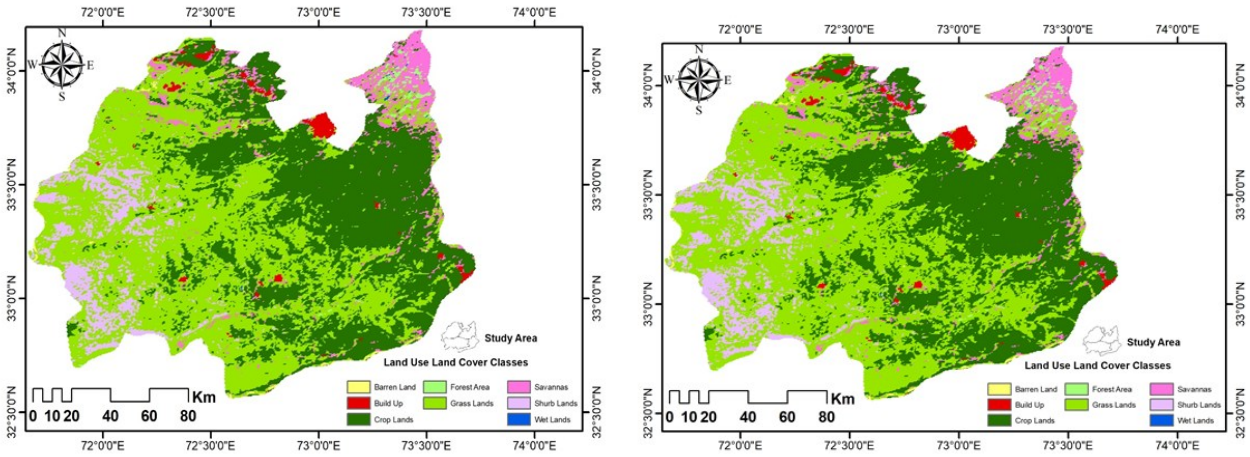


Figure 8: Land use land cover maps for the potwar region

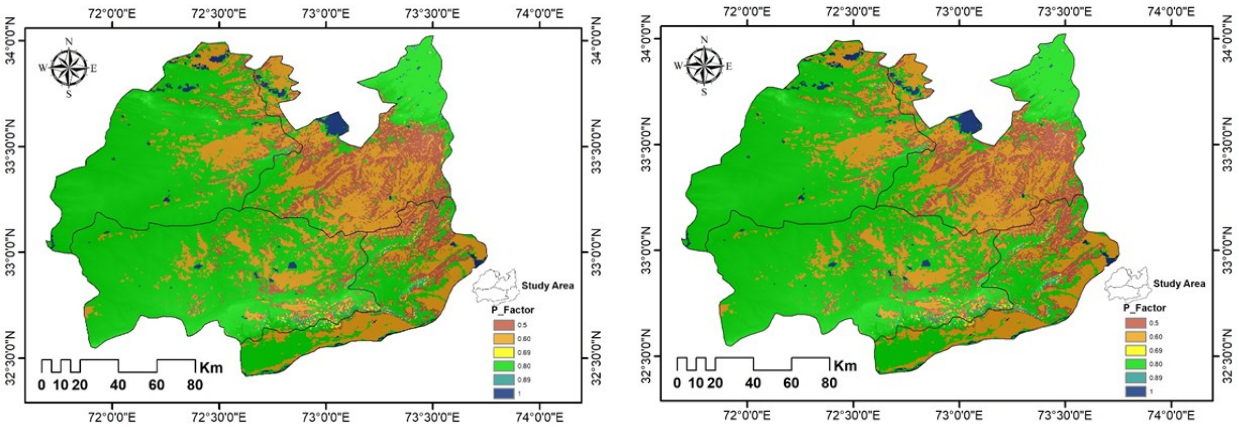


Figure 9: Support practice factor P factor for the potwar region

Land cover factor (C)

The C factor plays a significant role in crop management activities as it enables the determination of soil erosion risk and the effectiveness of conservation measures put in place. C values, computed from NDVI composites, ranged from 0.06 (dense vegetation) to 0.99 (bare land). The mean value was 0.45, with higher values observed in barren and low-vegetation zones across Attock and western Jhelum. The NDVI-based C map revealed vegetation heterogeneity across

Furthermore, it is discovered that built-up areas and scrubland offer comparatively fewer erosion threats, underscoring the significance of focused conservation efforts based on land-use features.

Support practice P factor

Based on the reports and field data from the Pakistan Metrological Department and the Department of Agriculture of the Government of Pakistan, the vicinity of the reservoir in the area of the study is reported to have been used for both

crops and other economic activities, and its vegetative cover (Tariq, 2023). The P component was estimated based on the approach and adapted using recent refinements introduced by using an equation proposed by Ahmed *et al*. (2013) and Sud *et al*. (2024) which ranged from 0 to 1 for slope, Figure 4, and LULC Figure 8, which were created from Digital Elevation Model (DEM) and Moderate Resolution Imaging Spectroradiometer (MODIS).

Through the MODIS data, eight land use classes have been identified. All these classes are components of the total land cover (P) factor that ranges from 0 to 1, where the 1 value indicates a strong possibility of soil erosion. Erosion sensitivity is most prominent in agriculture, grassland, and bare/sparse vegetation. The areas specific to each land use type are shown in Table 2. P values ranged from 0.5 to 1.0, with an average of 0.83. Croplands on steep slopes (>15%) showed the highest P values (0.8–1.0), indicating minimal conservation practices, while well-managed agricultural zones on gentle slopes were assigned lower values (0.5–0.6) (Figure 9). The P factor value depicted in Figure 9 gives an effective way of inferring the direction in which erosion control measures should be focused, as well as how the existing practices should be improved. By determining various tires of conservation effectiveness and the related erosion problems, stakeholders can target intervention strategies aimed at curbing soil erosion as well as putting in place sustainable land management practices across the Potwar region.

Table 2: LULC classes area

Class Name	Area in Sq km	Area in %
Forest Area	140.6462793	0.633%
Shrub Land	1542.234834	6.943%
Savannas	1193.566367	5.373%
Grass Land	10641.28778	47.903%
Wetlands	10.5153804	0.047%
Crop Lands	8361.467098	37.640%
Build up	260.0682413	1.171%
Barren Land	64.60327029	0.291%

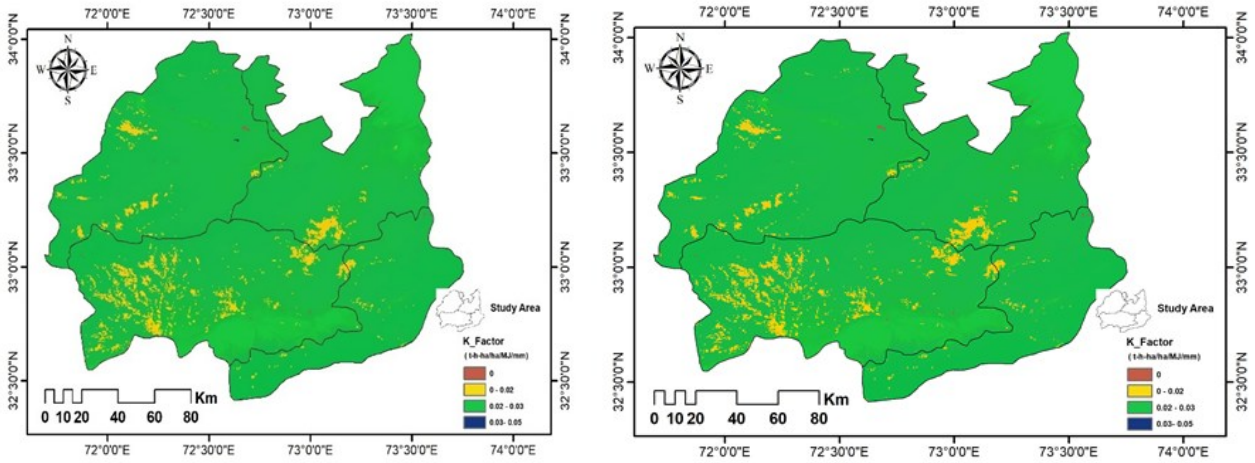


Figure 10: Soil erodibility K factor map for Potwar region (t·ha·h ha^{-1}·MJ·mm), based on OpenLandMap texture classes

Table 3: Soil loss classes and area

Class	Soil Loss (t ha^{-1} year^{-1})	Area (km²)	% of Total Area
Slight	< 10	2442	11.13%
Moderate	10–25	14882	67.80%
High	25–50	3380	15.40%
Very High	50–100	733	3.34%
Severe	>100	1778	8.10%

Soil erodibility K factor

This seasonal variability in the spatial distribution of K factors accentuates the differences in soil types that exist in the watershed. Soils with high K-value erodibility are usually associated with weak structure, low organic matter, and high proportions of silt or fine sands. On the contrary, K values that are low indicate soils that are not highly erodible and are often associated with high organic matter content, a well-developed soil structure, and sand, silt, and clay particles in proper proportions. Figure 10 illustrates that K-factor values were assigned from soil texture classes, ranging between 0.018 and 0.042 t·ha·h/ha·MJ·mm, with a mean of 0.031. Higher erodibility was observed in silt-dominated soils near central Potwar. The spatial pattern of the K-factor reinforces the role of weakly structured soils in elevating erosion risk. Incorporation of the K factor into the RUSLE model helps strengthen and understand soil erosion rates and their distribution throughout the region. The values of K from 0 to 0.05 confirm the importance of selecting specific properties of soil that need to be considered during the design and the application of effective erosion control measures. This information is critical to developing plans that deal with sensitive areas prone to erosion while promoting sustainable land use practices.

Soil erosion

The assessment of soil erosion in the Potwar region indicates a high degree of variability from 0 to 475 tons per hectare per year (with a mean of 42.8 t ha^{-1} year^{-1} and a standard deviation of 38.7), as shown in Figure 11. It is especially

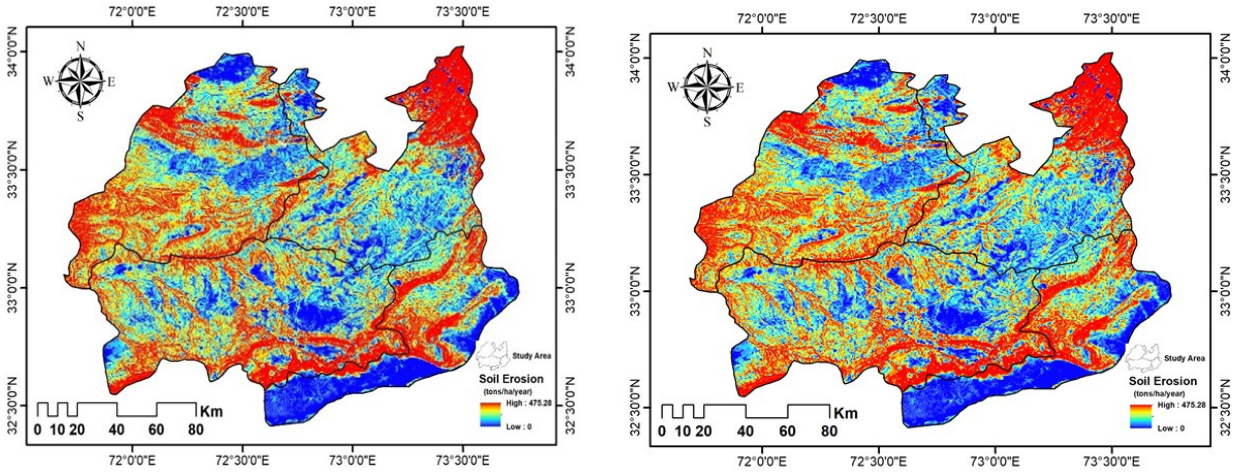


Figure 11: Annual soil erosion map of the Potwar region (t ha^{-1} year^{-1})

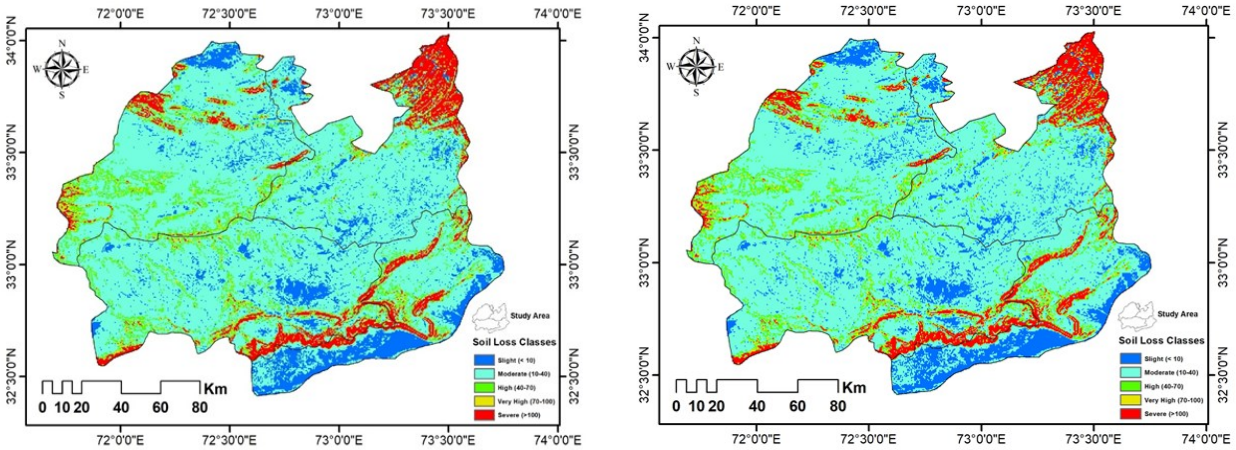


Figure 12: Soil loss severity classification map of the Potwar region

interesting to note that Rawalpindi experiences the most soil erosion, followed in order by Chakwal, Attock, and Jhelum. Based on literature thresholds (Renard *et al*., 1997; Jodhani *et al*., 2023), different classes of soil erosion range from slight to severe, and all of them have different degrees of susceptibility: mild, moderate, high, very high, and extremely severe. The areas of the region are classified as experiencing slight soil erosion, accounting for 11.13% of the region, or roughly 2442 km^2. In contrast, the moderate class encompasses 67.80 percent of the watershed area, or approximately 14882 km^2. This suggests that there is some soil loss in this region, and consequently, some conservation measures should be implemented. Areas with high erosion, which comprise about 15% of the total area or 692 km^2, require other remediation measures and swift action. In addition, there are 9.82% of the watershed area that requires the most attention due to potential soil erosion. Such a class displays the most prominent feature on the landscape, which is severe soil erosion with a watershed area proportion of 8.10%.

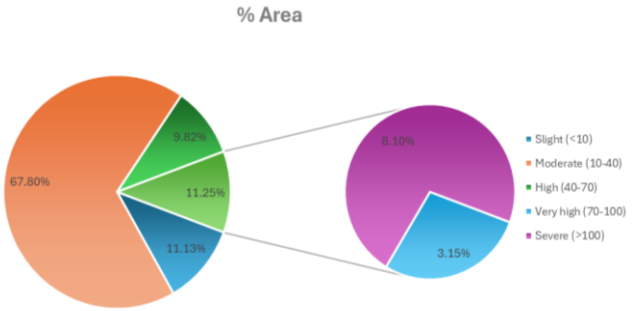


Figure 13: Percentage Area for soil loss classes

It is evident from these results that in sobering circumstances, well-planned and coordinated measures to mitigate soil erosion need to be implemented. To facilitate effective land use and environmental conservation in the Potwar area, soil and policy administrators need to design and implement conservation strategies that focus on the different severities of soil erosion. The significance of the findings presented in the figures is to inform policies directed towards the preservation of the environment and the intensity of the conservation measures. The loss of soil within a year in this region is approximately 46 metric tons per hectare. It has been proposed that the region surrounding the watershed of the river be divided into five erosion classes, ranging from low to severe, as shown in Figures 12 and 13. Soil loss was classified into five severity levels, are shown in Table 3.

Discussion

This study presents a robust and scalable assessment of soil erosion dynamics across the Potwar Plateau, employing a cloud-based RUSLE model on the Google Earth Engine (GEE) platform. The spatial patterns of soil loss reflect a strong correlation with environmental drivers such as rainfall intensity, slope gradient, sparse vegetation cover, and soil erodibility. Notably, erosion rates exceeded 100 t/ha/year in several northwestern upland zones, where topography is steep and vegetation is minimal. These results are consistent with previous findings from (Ullah *et al*., 2018)and (Borrelli *et al*., 2017), who similarly identified Rawalpindi and Chakwal as erosion hotspots due to their physiographic and climatic exposure. Comparable trends have been documented globally in semi-arid regions, such as the Loess Plateau in China (Zhang *et al*., 2013) and the Deccan Plateau in India (Kayet *et al*., 2018) where slope length and rainfall erosivity jointly govern erosion severity.

A key finding of this study is that approximately 8.1% of the region, equivalent to around 1,778 km² is classified as severely eroded, while over 67% of the land experiences moderate erosion. These values highlight the urgent need for spatially targeted conservation practices. Croplands on slopes above 15%, often lacking adequate soil retention strategies, were found to have the highest erosion risk. The observed patterns underscore the interaction between anthropogenic land-use pressures and natural topographic vulnerability. This finding is particularly relevant in the context of rapidly expanding agriculture and urbanization in Potwar, which disrupts soil stability and magnifies erosion hazards. Our use of MODIS-based land use and Sentinel-2 NDVI datasets provided reliable insights into vegetative cover and land management, validated through a classification accuracy of 85.6% and a Kappa coefficient of 0.81.

From a policy standpoint, the study offers a replicable framework for watershed prioritization and sustainable land planning. The delineation of soil loss severity zones can guide the allocation of resources for interventions such as afforestation, contour farming, and check dams in high-risk areas. These management strategies align with the best international practices proposed by FAO (2015) and contribute to broader sustainable development goals, especially SDG 15 (Life on Land) and SDG 13 (Climate Action). Furthermore, the GEE-based workflow demonstrated here is both time-efficient and computationally sustainable, overcoming traditional barriers of large-scale erosion modeling, such as data scarcity and processing power.

However, it is important to acknowledge several limitations of this study. The assignment of P and K factors relied on generalized literature values and global soil databases, which may not fully capture the local heterogeneity of conservation practices or subsoil

characteristics. Similarly, the MODIS LULC product, though widely used, has a native resolution of 500 meters and was resampled to 30 meters, introducing potential classification uncertainty in land cover mosaics or transition zones. The C-factor, derived from annual NDVI averages, may not reflect seasonal vegetation fluctuations, especially during peak monsoon or dry periods. Despite these limitations, the model remains a reliable proxy for erosion estimation, supported by validation efforts and sensitivity analyses. Despite the model's scalability and effectiveness, limitations exist. The P and K factors were generalized from literature and may not reflect localized conservation practices or soil heterogeneity. The use of resampled MODIS LULC (500 m to 30 m) may introduce classification error, especially in fragmented landscapes. NDVI-based C factor was computed as an annual mean, which may overlook seasonal variability. These factors introduce uncertainty that should be addressed in future high-resolution or ground-validated erosion assessments.

Looking forward, future research should aim to incorporate finer-resolution datasets from UAVs or commercial constellations like Planet Scope to enhance land cover and slope detection. Integrating machine learning algorithms into the GEE-based RUSLE framework could improve erosion susceptibility prediction by capturing nonlinear relationships among variables. In addition, field-based calibration of the K and P factors through soil sampling and local conservation mapping would improve model realism. These enhancements would help create adaptive, AI-supported early warning systems for soil degradation, enabling proactive land management across vulnerable regions like the Potwar Plateau and beyond.

Limitations

RUSLE is arguably one of the simplest and most efficient methods for estimating soil erosion loss from a given area (Haseeb *et al*., 2024). Its efficiency in regions with low information resources, like most developing countries, is a plus as it provides satisfactory estimates with minimum information use. Nonetheless, developed countries also utilize the RUSLE model extensively due to its flexibility and reliance on basic physical principles. Many other models are built out of complex empirical formulas that are normally wrong and inaccurate, unlike RUSLE, which is built out of basic physical principles. Despite the advantages, the application of RUSLE still has some limitations that need to be solved or improved. (Borrelli *et al*. (2021) draw attention to several drawbacks of the model, especially the dependency on accurate field data from rainfall, soil, land cover, and terrain features. This investigation experienced the same difficulties because accurate field data in the Potwar region was unobtainable, thus influencing the accuracy of soil erosion estimates. Moreover, direct application to Pakistan is problematic because RUSLE was developed based on datasets in the US. Expanding the data coverage for the specific region would help improve the model's precision by providing relevant key parameters and exact coefficients for its best use. In addition, RUSLE factors are neither amphitheater nor canyon stream erosion, which, together with other types, is important in soil degradation. The model predominantly addresses sheet and rill erosion, which skews the estimation of erosion processes to lower rates than are happening. In addition, RUSLE does not consider sediment deposition, sediment transport within the catchment area, or sediment export through the catchment area outlet, leading to a gross underestimation of soil erosion (Li *et al*., 2023). This underscores the necessity of developing new models that incorporate all the variables to measure soil erosion more accurately and meaningfully.

Conclusion

This study provides the first comprehensive, high-resolution assessment of soil erosion in the Potwar Plateau using the Revised Universal Soil Loss Equation (RUSLE) integrated with Google Earth Engine (GEE). The results reveal that 8.1% of the region is severely eroded, while nearly 68% experiences moderate soil loss, driven largely by steep slopes, minimal vegetative cover, and inadequate conservation practices. This study uses soil measurement techniques to assess areas highly susceptible to erosion in the Potwar region, which amounts to 8.20% or roughly 1,778 km² of the area. Results provide reliable data for the stakeholders and environmental practitioners to effectively manage watersheds and systematically plan the sustainable use of the land while preventing erosion. These findings underscore the urgent need for spatially targeted soil management interventions, especially in high-risk sub-watersheds. The cloud-based GEE approach demonstrated here offers a scalable, transparent, and reproducible method for large-area erosion modeling, overcoming traditional computational and data-access challenges. This workflow can be adapted to other semi-arid and erosion-prone regions globally. By providing detailed spatial outputs and classifying erosion severity zones, this research supports evidence-based policymaking and sustainable land use planning. It also aligns international soil conservation frameworks and helps advance SDG targets related to land degradation neutrality and climate resilience. Future studies should explore integrating machine learning models and high-resolution remote sensing datasets to further refine predictions and

enable dynamic, near-real-time erosion monitoring. Field-based validation of soil parameters and inclusion of socioeconomic factors will enhance model accuracy and policy relevance. Ultimately, this study contributes a powerful decision-support tool for regional planners, environmental managers, and policymakers aiming to combat land degradation and promote sustainable development.

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