



Spatial soil loss prediction impacted by long-term land use/land cover change: a case study of Swat District

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Abstract Soil erosion is a destructive consequence of land degradation caused by deforestation, improper farming practices, overgrazing, and urbanization. This irreversible effect negatively impacts the limited renewable soil resource, causing soil truncation, reduced fertility, and unstable slopes. To address the anticipation of erosion modulus resulting from long-term land use and land cover (LULC) changes, a study was conducted in the Swat District of Khyber Pakhtunkhwa (Kpk), Pakistan. The study aimed to predict and evaluate soil erosion concerning these changes using remote sensing (RS), geographic information systems (GIS), and the Revised Universal Soil

Loss Equation (RUSLE) model. We also evaluated the impact of the Billion Tree Tsunami Project (BTTP) on soil erosion in the region. Model inputs, such as rainfall erosivity factor, topography factor, land cover and management factor, and erodibility factor, were used to calculate soil erosion. The results revealed that significant soil loss occurred under 2001, 2011, and 2021 LULC conditions, accounting for 67.26%, 61.78%, and 65.32%, falling within the category of low erosion potential. The vulnerable topographical features of the area indicated higher erosion modulus. The maximum soil loss rates observed in 2001, 2011, and 2021 were $80 \text{ t/ha}^{-1}/\text{year}^{-1}$, $120 \text{ t/ha}^{-1}/\text{year}^{-1}$, and $96 \text{ t/ha}^{-1}/\text{year}^{-1}$, respectively. However, the observed reduction in soil loss in 2021 as compared to 2001 and 2011 suggests a positive influence of the BTTP on soil conservation efforts. This study underscores the potential of afforestation initiatives like the BTTP in mitigating soil erosion and highlights the significance of environmental conservation programs in regions with vulnerable topography.

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Introduction

Soil erosion is a critical environmental concern due to its adverse effects on soil productivity and nutrient depletion. Globally, agricultural production, water

infrastructure, and recreational spaces are all negatively impacted by land erosion, which costs about \$7 billion annually (Borrelli et al., 2020; Hewett et al., 2018). Furthermore, it worsens the issue by adding to the accumulation of sediment in aquatic environments (Pal et al., 2021). This profoundly affects agriculture, water storage facilities, and recreational areas, increasing flood hazards and infrastructure damage due to sediments (Alewell et al., 2020; FAO, 2011; Wuepper et al., 2020; Yang et al., 2003). Soil erosion has far-reaching effects on human health and the economy, especially in agriculturally dependent underprivileged groups. As a result, this problem must be fixed to lessen its impact on the natural world and people's quality of life (Waseem et al., 2023). Land degradation has worsened during the previous century, leading to the worldwide loss of 24 million t of topsoil productivity (Saif Ullah et al., 2022). The UN Food and Agriculture Organization projects that 90% of the world's topsoil will be at risk by 2050, highlighting the critical need for sustainable land management practices (FAO, 2019). Water-induced soil erosion is a pressing problem, second in importance only to global warming (Terranova et al., 2009; R Lal, 2021). Heavy rains, vulnerable terrain, overgrazing, and human activities contribute to this issue, which poses a serious threat to the northern parts of Pakistan. Overpopulation makes problems like deforestation for agriculture and the mining of wood and other resources even worse (Kheir et al., 2008; Nekhay et al., 2009; Tongde et al., 2021). Unfortunately, human activities are primarily responsible for soil degradation, which has recently emerged as a critical issue (Wiejaczka et al., 2017). These acts have affected each facet of land usage and can be further aggravated by natural factors, such as changes in the landscape and climate (Kriegler et al., 2013). The alteration of natural vegetation is the first obvious effect of these acts, and it has multiple ecological consequences (Bucala et al., 2015). Changing land usage from natural vegetation to agriculture has exacerbated the issue, especially in hilly locations. Due to intensive agricultural production, soil erosion rates have risen dramatically due to this shift in land use. Because of this, both the environment and the economy are in grave danger (Nearing et al., 2017).

In recent times, various countries across the globe have launched large-scale forest tree plantation initiatives within their respective regions as part of their

efforts to mitigate the effects of global warming. A notable example is the Government of China, which has reportedly redeployed over 60,000 workers to engage in extensive tree planting activities aimed at combatting pollution and expanding the nation's forest cover. In 2017, a remarkable conservation effort in India saw volunteers successfully plant a staggering 66 million trees within just 12 h, setting a remarkable record for a mass tree-planting drive. This monumental campaign involved the participation of approximately 1.5 million individuals who came together to plant saplings along the banks of the Narmada River in the province of Madhya Pradesh. In 2018, Bangladesh initiated a nationwide tree planting campaign as part of its comprehensive strategy to address and combat environmental changes within the region. The government's ambitious plan involved planting a total of 3 million trees across the country, coinciding with the National Tree Plantation Campaign and Tree Fair-2018 (Kamal et al., 2018). In 2014, the Khyber Pakhtunkhwa (KP) Forest Department launched the Billion Tree Tsunami Afforestation Project (BTTAP), which was successfully completed in November 2017, adhering to the guidelines established by the KP forest policy and forest ordinance of 2002 (Shah, 2018). This project was strategically designed to align with the Green Growth initiative in the forestry sector of the KP Province (Haris, 2023). The primary objective of BTTAP was to make a significant contribution towards mitigating the impacts of global warming in Pakistan, a country that ranks seventh on the list of nations most susceptible to climate change. The regions that benefited most from this initiative were the southern and central regions, encompassing the Malakand and Hazara divisions, which are prominent forested areas within the province (Report, 2016). The Billion Tree Tsunami Afforestation Project spanned the entire province and was divided into Phase 1, with a total cost of Rs. 1912.0 million, implemented during 2014–2015, and Phase 2, successfully completed between 2015 and 2017, with a total cost of Rs. 2422.72 million (Haris, 2023; Shafeeque et al., 2022).

Every year, the world's reservoirs lose between 0.5 and 1% of their storage capacity due to sedimentation, according to a study by Chuenchum (Chuenchum et al., 2020). It is not very comforting to think that most dams will have only half their current capacity by the 2050s (Chuenchum et al., 2020). Reports

indicate that in Asia, sedimentation consumes up to 40% of reservoir storage capacity, posing a significant threat to the reliability of water supplies in the future (Des E. Walling, 2011). Previous studies show that developing nations have a greater risk of soil erosion. Water erosion, for instance, affects about 30–32.8 million ha in India (Rattan Lal, 2017). According to a recent study (Mohammadi et al., 2018) conducted in Iran, the country loses an average of 1.6 t of soil per hectare each year. Similarly, in Pakistan, water erosion is responsible for soil loss on over 11.2 million ha (nearly 70%) of the country's total land area (Ashraf et al., 2017). There is a yearly sediment production of around 20 billion t from the world's largest rivers, with 80% of that going straight into the seas (D. E. Walling, 1988).

Traditional soil erosion assessment techniques via field surveys are laborious, time-consuming, and costly (Ganasri & Ramesh, 2016). To better determine the severity of soil erosion and quantify soil loss, it is preferable to apply numerical evaluation approaches to design regional management programs. This offers an alternate method for assessing land management strategies in gauged and ungauged basins and investigating and simulating land use activities' long-term and short-term effects on the natural system (Fistikoglu & Harmancioglu, 2002). Effective use of land resources can also result from the development of numerous land use scenarios and the assessment of their results using soil erosion models (Batista et al., 2019; De Jong et al., 1999; Prasad & Tiwari, 2022). Scientists have developed and deployed numerous models for over 70 years to predict and prevent soil erosion. These include the "Water Erosion Prediction Project" (WEPP) (Boardman, 2006; Choudhury et al., 2022; Lew et al., 2022), the "Soil and Water Assessment Tool" (SWAT) (Boardman, 2006; de Oliveira Serrão et al. 2022), the "Revised Morgan and Finney model" (RMMF) (Morgan, 2001), the "Soil Erosion Model for Mediterranean Regions" (SEMMED) (Boardman, 2006), and the "European Soil Erosion Model" (EUROSEM) (Boardman, 2006). The most popular empirical model for estimating soil erosion is the "Universal Soil Loss Equation" (USLE), which has a moderate level of complexity relative to other available models (Ganasri & Ramesh, 2016). To better anticipate soil erosion, scientists in the early 1990s updated and digitized the USLE model, resulting in the "Revised Universal Soil Loss Equation" (RUSLE)

(Kebede et al., 2021; Koirala et al., 2019; Panagos et al., 2021). The USLE and RUSLE (Kimberlin & Moldenhauer, 1977) are both often utilized in a variety of circumstances all around the globe. There are three types of erosion models: physical, conceptual (with some empirical components), and purely intellectual (Jha & Paudel, 2010). For almost 80 years, researchers have relied on the RUSLE model because of its high accuracy, flexibility, correctness, and simplicity of use and application (Aslam et al., 2020; Boardman et al., 2009; Dutta et al., 2015; Meliho et al., 2020; Morgan et al., 1984; Sandeep et al., 2021; Whittington, 2002).

This research is dedicated to evaluating the impact of the Billion Tree Tsunami Project (BTTP) on soil erosion within the Swat region, introducing a pioneering assessment of actual and potential soil loss associated with BTTP in Pakistan. Employing the RUSLE model and geo-information systems, our study aims to quantify soil erosion while explicitly considering the influence of BTTP. Beyond mere quantification, our research endeavors to create detailed maps that vividly depict the extent and severity of soil erosion throughout Swat, accounting for the dynamic changes brought about by BTTP and other relevant factors. These maps will serve as invaluable tools for informed policymaking in the region, particularly considering conservation efforts and land management practices that bear the imprint of BTTP. This research sets the groundwork for the development of future soil and water conservation policies in Pakistan, incorporating the lessons gleaned from BTTP into a broader framework for sustainable land use and environmental preservation.

Methodology

Study area

The Swat District, located at 34°46'58" N latitude and 72°21'43" E longitude is in Khyber Pakhtunkhwa (KpK), Pakistan. Its northern border is with Chitral, its western border is with Dir, and its northeastern border is with Gilgit-Baltistan. There are 1.26 million people that live in the district, which is 5337 km² in territory (Bangash, 2012; Atta-ur-Rahman and Khan 2011). The research area is located in the heart of KpK tourist industry and is a mountainous

region surrounded by the Hindu Kush Himalayas (Qasim et al., 2013). The climate of Swat ranges from semiarid to subhumid to humid (Tariq, 2022; Zamani et al., 2022). The research area is located within a suture zone (S.Z.) formed by the collision of the Indian Plate and the Kohistan Island Arc (KIA) from a geological perspective. The S.Z. is situated on the northern side and is the most active tectonic and geomorphic region where the KIA meets the Asian Plate (Islam et al., 2022; Waqas et al., 2021). Annual precipitation ranges between 600 and 1200 mm in the research region (Bazzani, 2013; Dahri et al., 2011). Most of the population relies on natural assets, including farmland, pasture, cattle, fisheries, vacation spots, and timber, for their livelihoods (S. R. Khan &

Khan, 2009). Approximately 42% of the local population relies on agriculture for their income (Bacha et al., 2021).

The protected woods and rich soils of Swat have made it famous. Swat's forest cover accounts for around 20% of the district's total area, or 165,638 hectares (Bacha et al., 2021; Bazzani, 2013). Swat has been densely wooded since prehistoric times, and its cedar forest was formerly considered the best in the world (S. R. Khan & Khan, 2009). Khyber Pakhtunkhwa's rural residents rely heavily on the province's forest resources. Most of the population relies on these materials for shelter, food, and transportation (Sajjad et al., 2015). Figure 1 illustrates the location of the study area in relation to

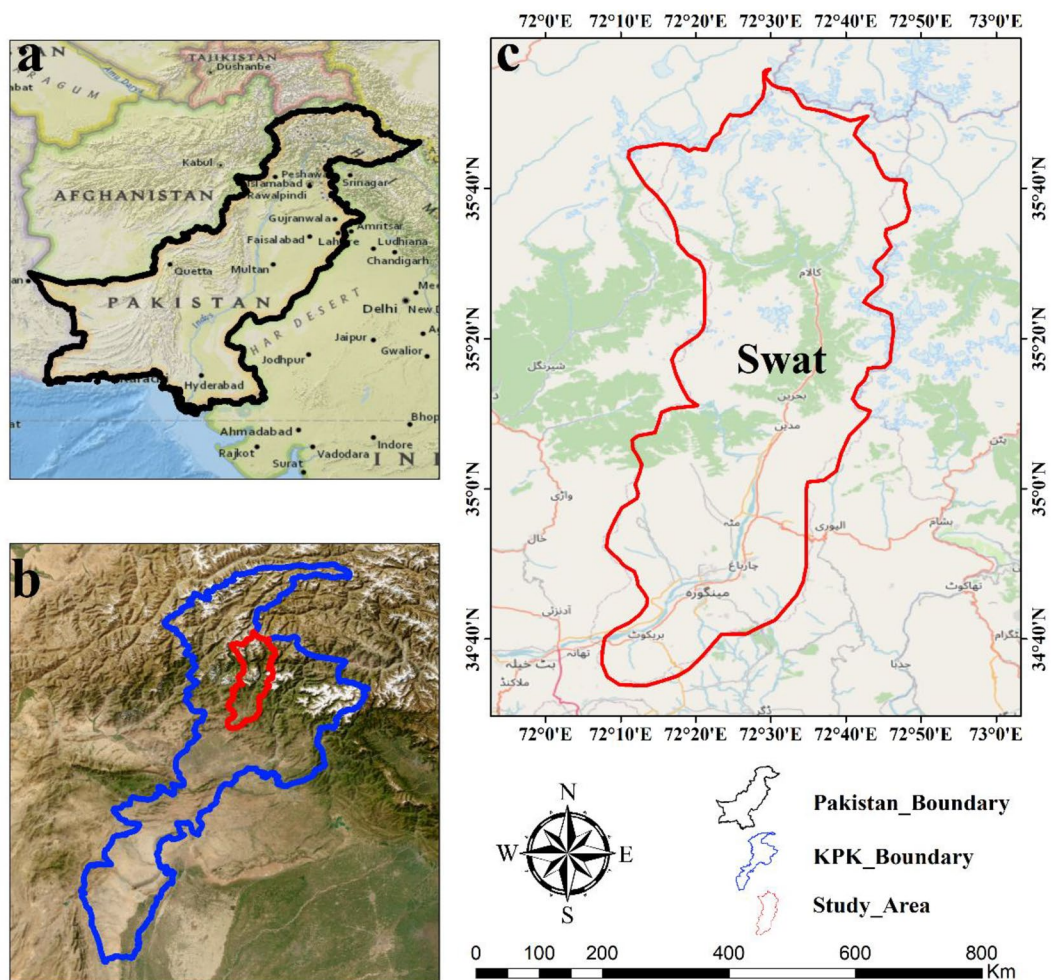


Fig. 1 Detailed study area map, **a** map of Pakistan, **b** map of Khyber Pakhtunkhwa Province indicating the study area location, and **c** map of the study area (Swat District)

Pakistan, providing a visual representation of its geographical position. Additionally, Fig. 2 presents a digital elevation model and slope analysis of the study area. This analysis reveals that the study area is characterized by high elevation, with the highest point reaching an altitude of 5828 m. The figure effectively conveys the topographic features of the study area, highlighting its mountainous nature and emphasizing its significance as a highly elevated region within Pakistan.

RUSLE model for soil prediction

The Revised Universal Soil Loss Equation (RUSLE) is a widely used model for studying soil erosion. It considers various factors, both direct (like slope length, steepness, rainfall erosivity, and soil erodibility) and indirect (like crop management and soil conservation practices) (Wang et al., 2022). This model helps create maps to better understand soil erosion in specific areas (Alitane et al., 2022; Doulabian et al., 2021).

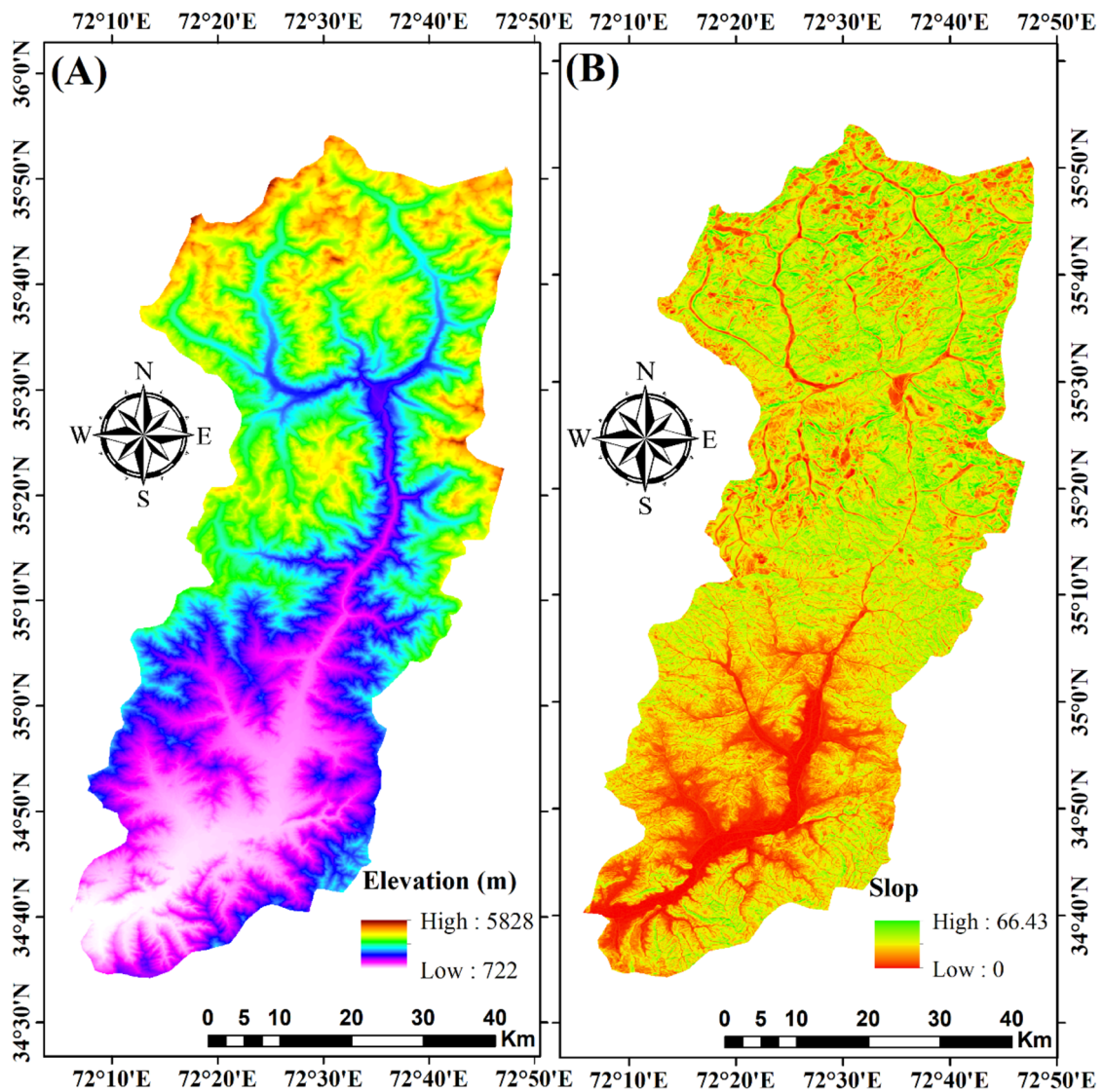


Fig. 2 Digital elevation model (A) and slope (B) of the study area

This research generated a land cover map from satellite imagery, soil types, and farming techniques, and then, the RUSLE model was applied to the data. The model's adaptability to GIS makes it useful for this investigation because it allows for more precise analysis. Figure 3 shows the procedure in this study; the RUSLE equation (Eq. (1)) was derived by merging five input factors connected and sensitive to spatial and temporal fluctuations. Erosion is calculated on a pixel-by-pixel basis due to the interdependence and spatial variability of the input data.

$$A = R \times K \times LS \times C \times P \quad (1)$$

where A is the annual soil erosion rate ($t \text{ ha}^{-1} \text{ y}^{-1}$), R is the RE factor ($\text{M.J. mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$), and K is the S.E. ($t \text{ ha}^{-1} \text{ h MJ}^{-1} \text{ ha}^{-1} \text{ mm}^{-1}$), and the other parameters are dimensionless (Fig. 3). Soil erosion was estimated empirically using ArcGIS's raster map tool after these five components were added separately.

Using ArcGIS's spatial function, we defined the scope of our investigation. ArcGIS 10.8 was used to process all the spatial data. Table 1 displays the estimated RUSLE parameters and the corresponding digital elevation model data source.

Rainfall erosivity (RE) factor R

This component justifies the total amount and severity of annual rainfall. From the Pakistan Meteorological Department, we gathered monthly precipitation data for 3 years (2001, 2011, and 2021) at each of the five weather stations in the research area. The requirement for certain data makes it somewhat challenging to estimate this element. Because of all the confusion, simple processes were developed. This analysis determined the R-factor by applying the proposed model (Morgan, 2005) to the interpolated rainfall map using the provided equation. Saleem Ullah (Saleem Ullah

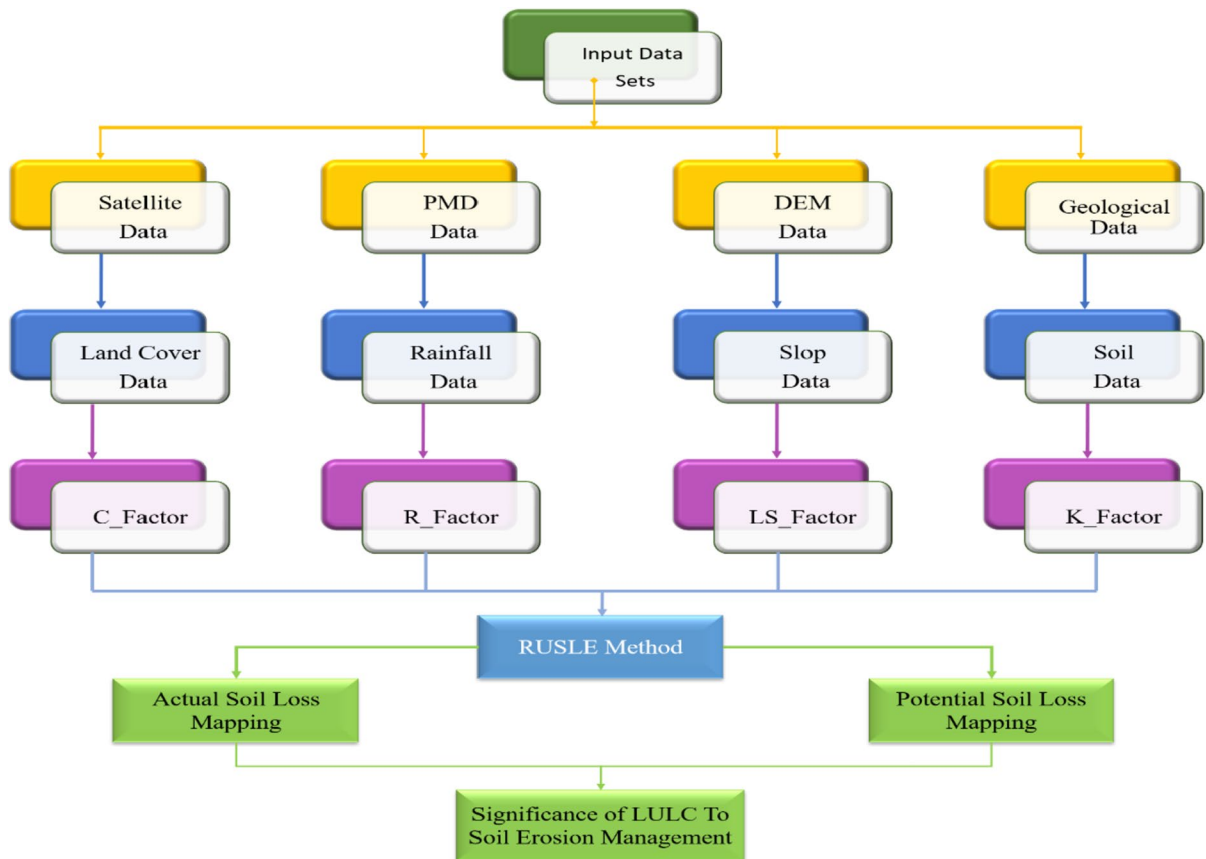


Fig. 3 Methodological framework (PMD Pakistan Meteorological Department, DEM digital elevation model)

Table 1 Source of the dataset used for this research

Serial no	Data type	Data description	Data source
1	Digital elevation model (DEM)	Global SRTM DEM with a resolution of 30 m per arc second	U.S. Geological Survey: Earth Observation and Science (“USGS EROS Archive—Digital Elevation—Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global U.S. Geological Survey” n.d.)
2	Soil data	Global FAO soil map with a resolution of 5×5	Food and Agriculture Organization (FAO-UNESCO, 1979)
3	Rainfall data	Monthly and yearly averaged rainfall data	Pakistan Meteorological Department (“Pakistan Meteorological Department” n.d.)
4	LULC data	MODIS land cover MCD12Q1 product	US Geological Survey: Earth Observation and Science (Gray et al., 2019)

et al., 2018) and Ahsen Maqsoom (Maqsoom et al., 2020) employed the same calculation, whose study area shares topographic features with ours.

$$R = 0.05 \times P \tag{2}$$

where P is the annual average rainfall in millimeters.

Figure 4 displays the rainfall patterns and rainfall erosivity factor (R) of the study area for three different years: 2001, 2011, and 2021. The figure provides a visual representation of the variation in rainfall and corresponding R factor values across these years. It is observed that the highest R factor values recorded were 36.80, 39.94, and 37.20 for the years 2001, 2011, and 2021, respectively. These values indicate the erosive potential of rainfall in the study area during those specific years. The figure allows for a comparison of rainfall and R factor variations over time, contributing to a comprehensive understanding of the study area’s hydrological characteristics and potential soil erosion risks.

Soil erodibility (S.E.) factor K

The soil erodibility factor (K) is a metric that measures how easily soil particles can be detached from their host soil and carried away by precipitation and runoff. The K factor is mostly determined by the soil’s texture, organic matter content, structure, and permeability. S.E. is the “rate of erosion per unit of the erosion index from a typical unit plot of 22.13 m in length with a slope gradient of 9%” (Ganasri & Ramesh, 2016). It reflects the rate of soil loss per erosivity of rainfall (R) index.

The original equation (Wischmeier & Smith, 1978), which required knowledge of soil structure and permeability value, was solved using the equation provided by (Sharpley & Williams, 1990). This equation was then used to estimate the erodibility of the soil.

$$K = Fcsand * Fsi - cl * Forge * Fhisand * 0.1317 \tag{3}$$

where

$$Fcsand = \left[0.2 + 0.3 \exp \left(-0.0256 SAN \left(1 - \frac{SIL}{100} \right) \right) \right] \tag{4}$$

$$Fsi - cl = \left[\frac{SIL}{CLA + SIL} \right]^{0.3} \tag{5}$$

$$Forge = \left[1.0 - \frac{0.25C}{C + \exp(3.72 - 2.95C)} \right] \tag{6}$$

$$Fhisand = \left[1.0 - \frac{0.70SN1}{SN1 + \exp(-5.51 + 22.9SN1)} \right], \tag{7}$$

where C is the percentage of organic matter content, SN1 is the sand content, and CLA, SIL, and SAN are the percentages of sand, silt, and clay, respectively.

Fcsand soils that contain an abundance of coarse sand have a relatively low erodibility, while soils that contain much fine sand have a high value.

Fsi-cl The soil’s clay-to-silt ratio is high, resulting in a low erodibility factor.

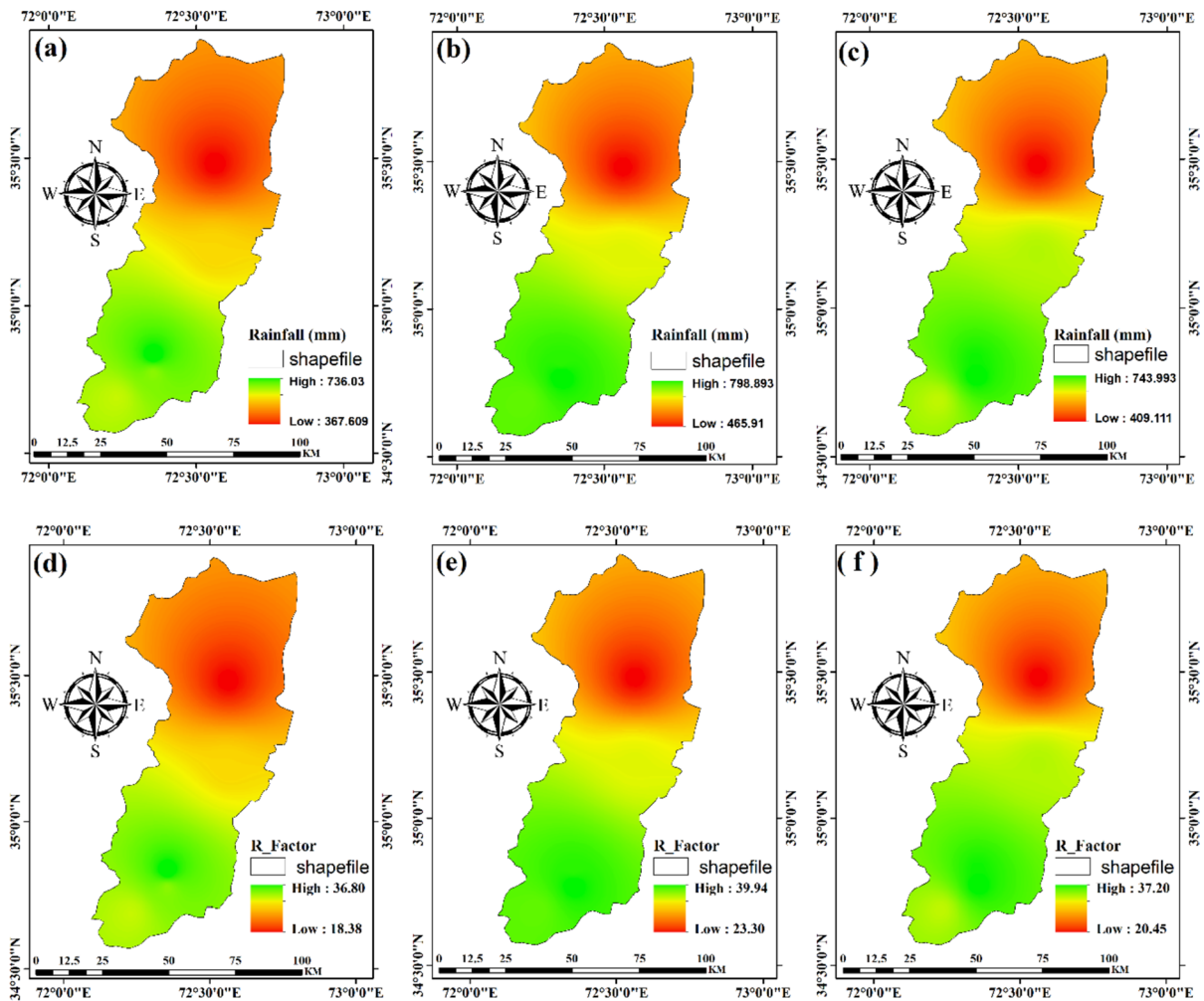


Fig. 4 Annual rainfall and R-Factor for the years 2001, 2011, and 2021. **a** Rainfall for 2001, **b** rainfall for 2011, **c** rainfall for 2021, **d** R-Factor for 2001, **e** R-Factor for 2011, and **f** R-Factor for 2021

Forgc This aspect reduces erosion for soils rich in organic matter.

Fhisand This factor indicates that erosion will decrease for extremely sandy soils.

Soil types and their respective K factor is shown in Fig. 5.

Topographic L.S. factor

The L and S variables in RUSLE stand for the influence of topography affecting erosion rate. Soil erosion and overland flow increase with greater slope

length and steepness (Siswanto & Sule, 2019). Furthermore, variations in slope have a far larger effect on cumulative soil loss than variations in slope length (McCool et al., 1987). The topography becomes a decisive element when the ground slope exceeds the critical angle. Using the DEM in the ArcGIS setting allowed us to calculate the L.S. value. The DEM is crucial in determining the L.S. factor since it details the length and steepness of the slopes on the landscape. When calculating L.S., it is important to consider factors like flow accumulation and slope steepness. We combined steepness and flow accumulation characteristics into the digital elevation model using the ArcGIS Spatial analyzer add-on. The runoff

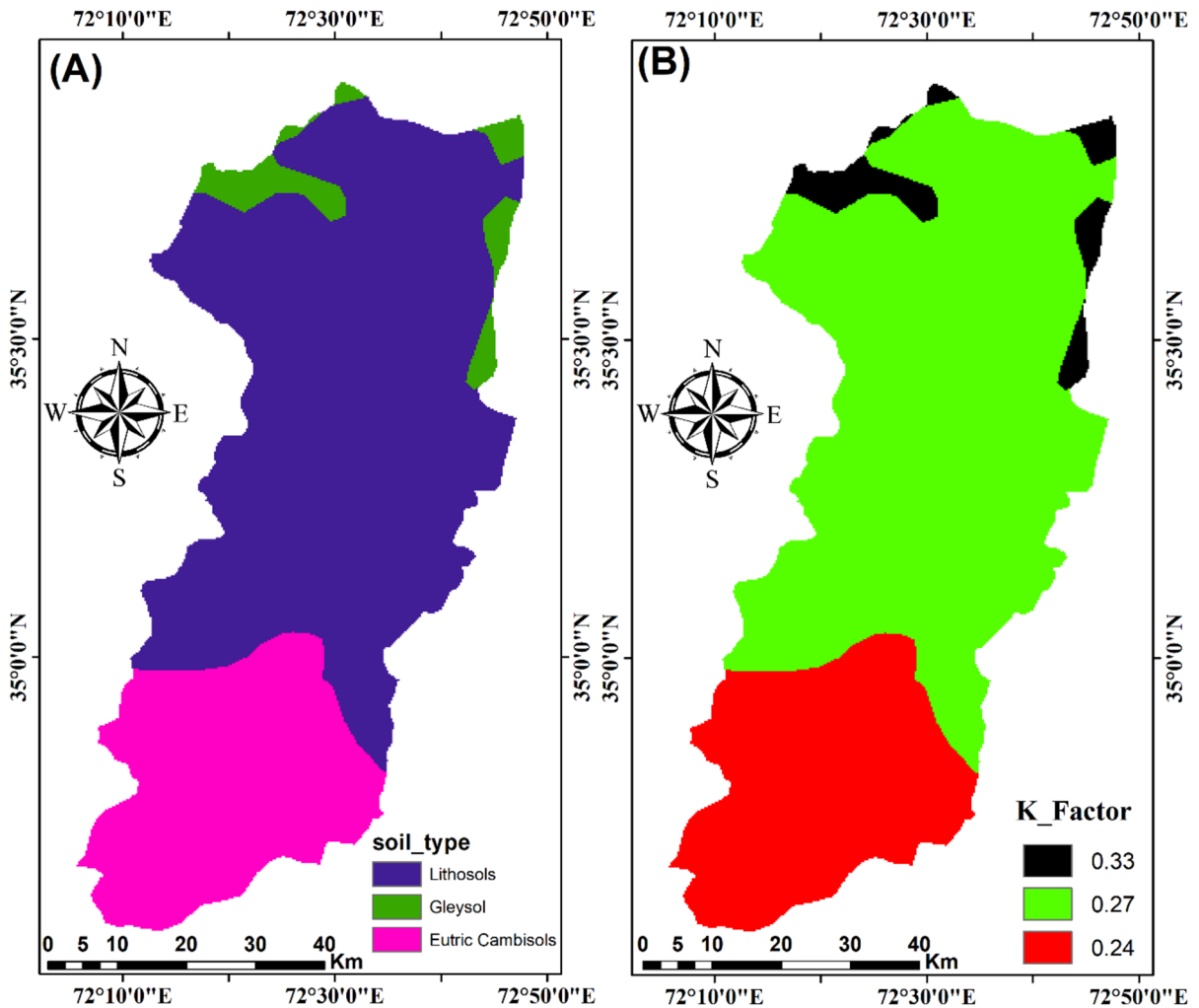


Fig. 5 Types of soil (A) and their respective K_Factor (B) in the Swat District

accumulation rate and the slop were calculated using this digital elevation model. Equation (8), proposed by Moore and Burch (I. A. N. D. Moore & Burch, 1986a, 1986b; I. D. Moore & Burch, 1986a, 1986b), was used to obtain the L.S. factor.

$$LS = \frac{(\text{Flow accumulation} \times \text{CellSize}^{0.4})}{22.13} \times \frac{(\text{SinSlope})^{1.3}}{0.0896} \tag{8}$$

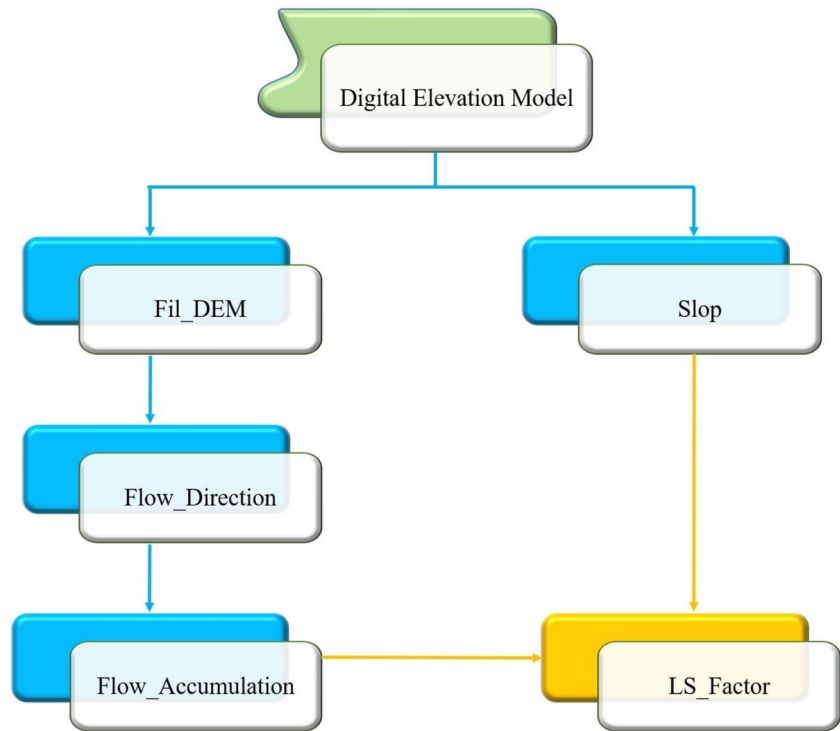
where “flow accumulation” is the grid cell’s total upslope supporting area, “L.S. factor” is a combination of length and steepness of slop. The “cell size” variable provides the size of a single grid cell, while the “sin slope” is in sin, indicating the slope’s degree. Figure 6 indicates a detailed breakdown of the L.S.

factor calculation, while Fig. 7 shows the LS factor for the Swat District provides a visual representation of the L.S. factor for the Swat District, highlighting the spatial distribution of erosion risk across the region.

Cover management factor (C)

Regarding soil loss, LULC classifications are characterized by the C factor. Information about soil management, the role of crop a, soil moisture, and soil surface variation are all required for calculating the C factor. However, there is a lack of data and many possible combinations, making it difficult to evaluate any of these characteristics (Farhan & Nawaiseh, 2015). In this investigation, we

Fig. 6 Flowchart for the estimation of topographic factor



employed LULC categorization to establish the C factor, following the guidelines of Yesuph and Dagnev (2019) and Fayas et al. (2019). We used the LULC map of the basin to get the C parameter. Then, using a literature-recommended procedure (Allafta & Opp, 2022; Maqsoom et al., 2020; Swarnkar et al., 2018), we vectorized the raster map to present the corresponding C factor for each LULC category. Figure 8 represents the LULC classification and C_Factor for 2001, 2011, and 2021. Table 2 presents the values for the cover management factor (C factor) ranging from 0 to 1. The C factor is an important parameter used in soil erosion modelling to estimate the susceptibility of an area to soil loss. In this table, higher values of the C factor indicate that the corresponding areas have a greater vulnerability to soil erosion. This implies that areas with higher C factor values have less effective vegetation cover or management practices, making them more prone to soil erosion processes.

Erosion control practice (P) factor

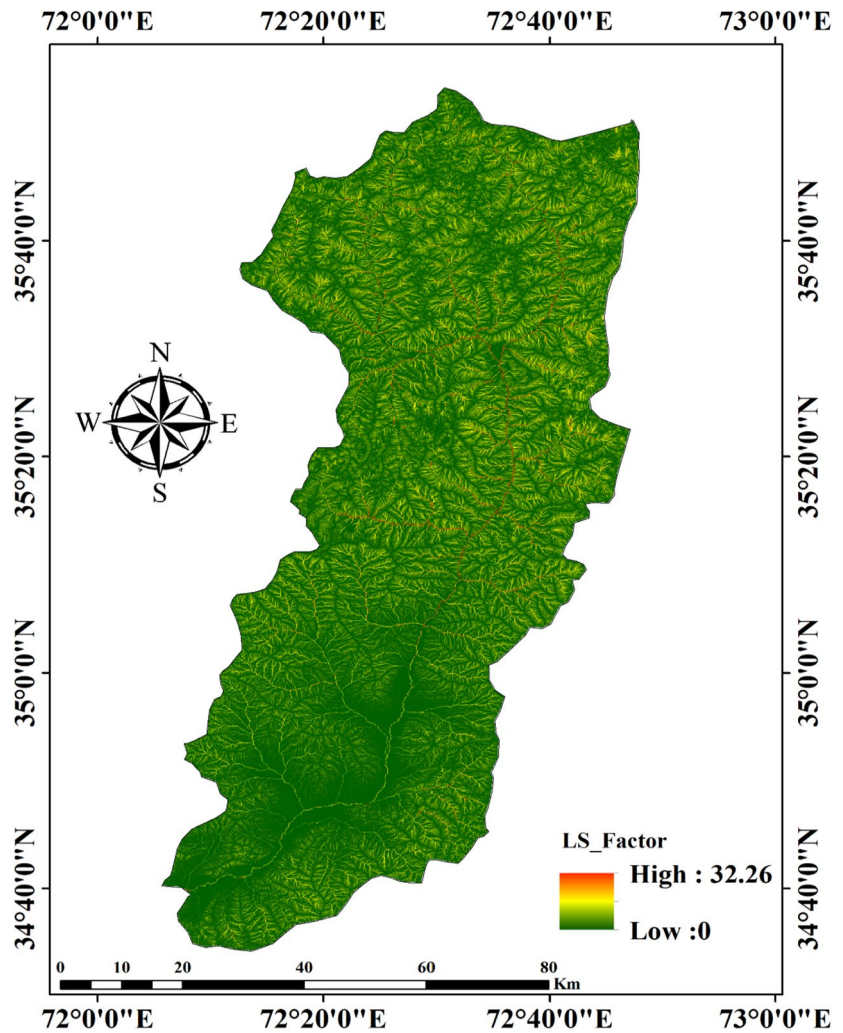
The P factor is the soil loss ratio to soil loss under a certain topographic condition under up-and-down-hill ploughing. Determining the P factor involves treatments

and precautions to keep free particles close to the source and stop their transit. Land treatments such as contouring, compaction, developing sediment basins, and constructing other structures to monitor and manage soil erosion all contribute to the P factor by acting as preventative measures against erosion. The methods used to lessen the impact of different major causes of erosion help determine this factor. Nothing has been done in Pakistan related to erosion control practices. Therefore, the P factor for the entire region was set to 1, signifying that no resistance strategies are being employed there (Batool et al., 2021; Maqsoom et al., 2020).

Actual and potential soil erosion prediction

The term “soil erosion prognosis” refers to an evaluation of both actual and potential soil erosion (Adinarayana et al., 1999; Pradhan et al., 2012; Rizzei et al., 2016). Actual soil erosion is the loss of soil that occurs due to natural or anthropogenic processes such as precipitation, runoff, wind, or tillage. Factors such as soil type, slope, land use, and management techniques affect how much soil erodes. All the factors of the RUSLE model, including R, K, C, P, and L.S., are utilized to predict actual soil loss.

Fig. 7 Topographic L.S. factor for Swat District



On the other hand, potential soil erosion is an estimate of the soil that could be lost if any conservation measures do not protect the area. Soil erodibility, slope, and land use are all included in estimating potential soil erosion. By removing the C and P variables, the RUSLE model can estimate the potential of soil erosion.

$$\text{Potential Soil Loss(A)} = R \times K \times \text{LS} \tag{9}$$

Result and discussion

Land use change dynamics analysis

Using ArcGIS 10.8, we analyzed land cover fluctuations in the Swat district between 2001 and 2011 and

201 and 2021. The study area, spanning 5360 km², was classified into seven land cover categories: grassland, bare area, cropland, natural trees, buildup area (human-made structures), water bodies, and snow. The land cover analysis was conducted for 2001, 2011, and 2021. The land use and land cover (LULC) classes, namely, savanna, shrubland, and forest areas, are classified as natural vegetation with natural tree cover. The prominence of land cover types in the study area followed a specific order, with grassland being the most prominent, followed by bare areas, cropland, natural trees, buildup areas, water bodies, and snow cover. The areas covered by buildup areas, snow cover, and water bodies are approximately equal in size. This order indicates these land cover types of relative distribution and abundance within the Swat

region. The thematic maps derived from satellite imagery provided a comprehensive understanding of the land cover changes over the past two decades. The composition and extent of each land cover category are summarized in Table 3. As indicated in Table 3 and Fig. 9, grassland and bare area have consistently been the two predominant land use classes throughout the study period. These two classes collectively cover a substantial portion of the study area, accounting for 59% in 2001, 59% in 2011, and 56% in 2021.

In 2021, the extent of grassland decreased to 1882.90 km², showing a decline from 1929 km² in 2011 and 1915.94 km² in 2001. This reduction represents a decrease of approximately 33.94 km² (approximately 3,395 ha) compared to the area observed in 2001. The area occupied by bare land is reduced to 1136.21 km² in 2021, compared to 1239.99 km² in 2011 and 1277.13 km² in 2000. This reduction indicates a decrease in bare land area over the study period. The decrease in the bare land could be attributed to various factors, including expanding buildup areas and initiatives Billion Tree Tsunami Project (BTTP). The cropland area also experienced a decrease during the study period. It was estimated to be 1176.70 km² in 2001, increased to 1202.40 km² in 2011, but then decreased to 1091.39 km² in 2021.

Table 2 C_Factor values for land use land cover classes

Sr. no	Land cover	C_Factor
1	Shrub/savana/grass	0.7
2	Forest cover	0.004
3	Water bodies	0
4	Crop land	0.65
5	Buildup area	0
6	Snow cover	0
7	Bare land	1

The reduction in cropland area could be attributed to various factors such as urbanization, conversion of agricultural land for other purposes, changes in land management practices, or shifts in agricultural patterns (Farah et al., 2019). The grassland area also experienced a decrease from 1915.94 km² in 2001 to 1882 km² in 2021.

In contrast to other land use classes, the area covered by natural trees in Swat Valley has increased

over the study period. The natural tree cover in the valley increased to 1066.42 km² (19.9%) in 2021, compared to 848.92 km² (15.8%) in 2011 and 875.99 km² (16.3%) in 2001. This increase in natural tree cover suggests positive changes in the area's vegetation dynamics and afforestation efforts. Observing an increase in natural trees raises whether this change can be attributed to the Billion Tree Tsunami Project (BTTP). The BTTP, launched in 2014 in Pakistan, aimed to plant one billion trees nationwide to combat deforestation and promote environmental sustainability (Kamal et al., 2018). Further analysis and research are required to ascertain the direct Impact of the BTTP on the increase in natural trees. This could involve assessing the trees' spatial distribution and age structure, analyzing the correlation between tree planting initiatives and the observed changes, and considering other factors such as climate and land management practices.

Water bodies in the area increased from 39.92 km² in 2001 to 40.89 km² in 2021, indicating a slight increment in the extent of water bodies over time. The area covered by Snow significantly increased from 32.94 km² in 2001 to 74.03 km² in 2021. Various factors, including changes in climate patterns and precipitation levels in the region, may influence this expansion in snow cover. Buildup areas, comprising human-made structures, experienced an increment from 41.38 km² in 2001 to 68.16 km² in 2021. This indicates an increase in urbanization and infrastructure development in the study area.

Spatial soil loss

The soil erosion patterns within the studied watershed exhibited some degree of spatial variation across the 3 years of the study. For simplicity's sake, we divide the soil-erosion-affected area into five distinct types. To pinpoint high-risk locations and develop efficient prevention tactics, precise quantification of soil erosion risks is essential.

A soil hazard categorization system was adopted based on the ranges defined by the OECD (Dqg & Wkh, 2000) and generally used in similar research in the region to evaluate the levels of soil danger in the study area. Several other studies in the same general area as the current one used a similar soil erosion classification system (Farhan & Nawaiseh,

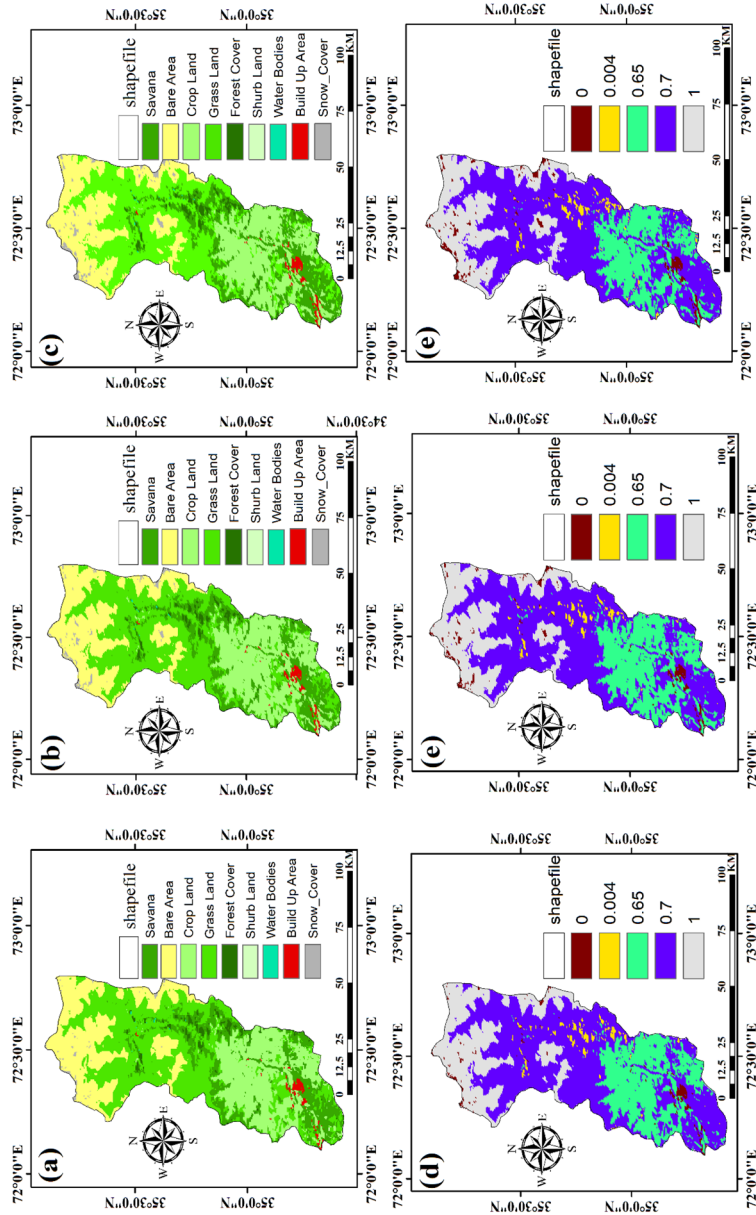
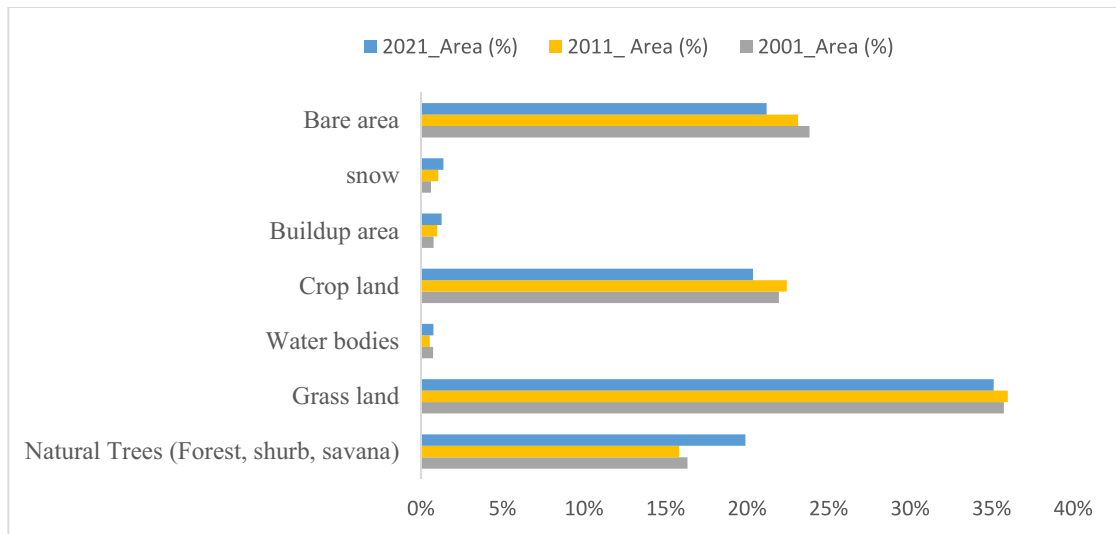


Fig. 8 LULC classification maps and their respective C_Factor values for the years 2001, 2011, and 2021 in the Swat District, Kpk, Pakistan. **a** LULC for 2001, **b** LULC for 2011, **c** LULC for 2021, **d** C factor for 2001, **e** C factor for 2011, and **f** C factor for 2021

Table 3 Land use changes from 2001 to 2021

Categories	2001		2011		2021	
	Area (%)	Area km ²	Area (%)	Area km ²	Area (%)	Area km ²
Natural trees (forest, shrub, savanna)	16.343%	875.99	15.838%	848.92	19.896%	1066.42
Grassland	35.745%	1915.94	35.989%	1929.00	35.129%	1882.90
Water bodies	0.745%	39.92	0.548%	29.37	0.763%	40.89
Cropland	21.953%	1176.70	22.433%	1202.40	20.362%	1091.39
Buildup area	0.772%	41.38	0.997%	53.45	1.272%	68.16
Snow	0.614%	32.94	1.061%	56.86	1.381%	74.03
Bare area	23.827%	1277.13	23.134%	1239.99	21.198%	1136.21

**Fig. 9** Land use land cover (LULC) trend from 2001 to 2021

2015; Bashir et al., 2013; Aslam et al., 2020). Classification involved dividing erosion rates into five groups: very low ($0-1 \text{ t ha}^{-1} \text{ year}^{-1}$), low ($1-5 \text{ t ha}^{-1} \text{ year}^{-1}$), moderate ($5-10 \text{ t ha}^{-1} \text{ year}^{-1}$), high ($10-50 \text{ t ha}^{-1} \text{ year}^{-1}$), and very high (more than $50 \text{ t ha}^{-1} \text{ year}^{-1}$).

Actual soil loss prediction

The analysis of the spatial distribution of actual soil erosion (Fig. 10, Table 4) in the Swat District reveals important findings. In 2001, the highest recorded soil erosion level was $80 \text{ t per hectare per year}$. This increased to $120 \text{ t ha}^{-1} \text{ year}^{-1}$ in 2011 but decreased to $95 \text{ t ha}^{-1} \text{ year}^{-1}$ in 2021. The fluctuation in extreme soil erosion levels suggests the region's dynamic

nature of erosion processes. Most of the area experienced very low or reversible soil loss, accounting for 67% in 2001, 62% in 2011, and 65% in 2021. This suggests that the erosion in these regions is minimal and can be easily recovered. Low soil erosion, ranging from 1 to 5 t per hectare per year, was observed in 22% of the area in 2001, 23% in 2011, and 21% in 2021. This indicates a slightly higher erosion level than the very low category but still within acceptable limits. The medium soil loss category, accounting for 8% in 2001, 11% in 2011, and 9% in 2021, signifies areas with moderate erosion levels. High soil loss, exceeding the previous categories, was observed in approximately 3% of the area in 2001, 2% in 2011, and 3% in 2021. Extreme soil loss, representing the highest erosion levels, accounted for 0.87% in 2001,

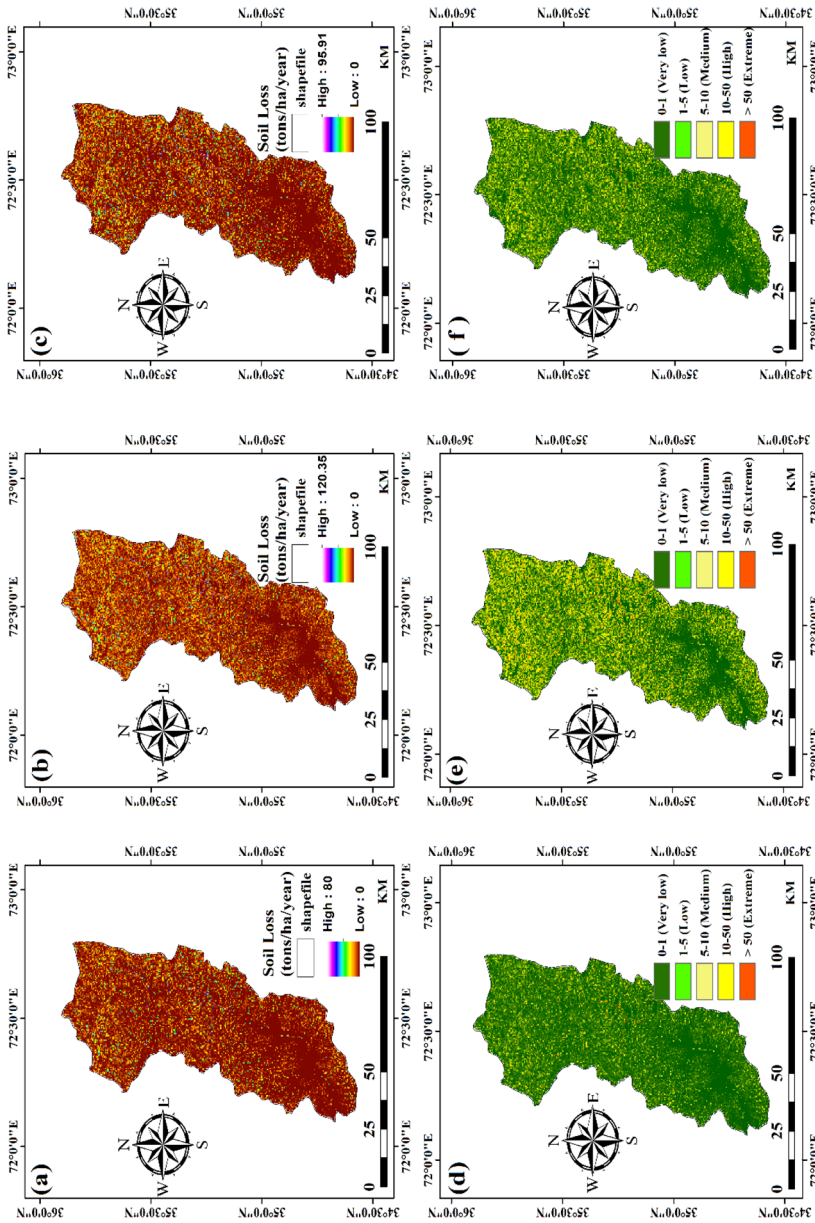


Fig. 10 Actual soil erosion and severity classes for the Swat District in 2001, 2011, and 2021. **a** Soil loss for 2001, **b** soil loss for 2011, **c** soil loss for 2021, **d** severity class for 2001, **e** severity class for 2011, and **f** severity class for 2021

2.12% in 2011, and 1.71% in 2021. Extreme soil loss indicates that these areas are particularly vulnerable to erosion and necessitate urgent measures to mitigate soil loss and prevent further degradation. One possible explanation for decreased soil erosion could be increased natural tree cover. The expansion of tree cover can help stabilize soil and reduce erosion rates. This finding is consistent with the objectives of the Billion Tree Tsunami project, which aims to increase tree plantation to combat deforestation and soil degradation. The findings of actual soil loss reveal significant variations in average soil loss rates over time. In 2001, the average soil loss was estimated at 21.32 t per hectare per year. This value increased to 29.67 t per hectare per year in 2011, suggesting a heightened intensity of soil erosion processes. However, by 2021, the mean soil loss decreased to 24.82 t per hectare per year, indicating potential improvements in soil conservation efforts or alterations in land management practices.

Prognosis

The prognosis conducted in this study involved comparing actual soil erosion maps with potential soil erosion maps. The analysis revealed that the potential soil erosion was higher than the actual soil erosion. This difference can be attributed to the absence of C (cover and management) and P (support practice) factors in the potential soil loss equation. In the potential soil loss equation, the C and P factors are assumed to equal 1. However, the C factor represents the land cover and management practices, while the P factor represents the support practices that protect the soil from erosion. By eliminating the C and P factors, decision-makers can better understand the potential extent of erosion in each area. Applying the potential soil loss equation to the study area assumes that soil loss is calculated for cleared land without considering land use and land cover (LULC) changes. This assumption leads to estimating a significant amount of potential soil loss due to the absence of protective land cover.

The analysis of potential soil loss (Table 5) revealed that a significant portion of the area had very low erosion levels, with percentages of 64% in 2001, 58% in 2011, and 62% in 2021. On the other hand, extreme soil loss, indicating the highest erosion rates, accounted for 1.85% in 2001, 3.86% in

2011, and 2.78% in 2021. Figure 11 indicating that in 2001, the maximum potential soil erosion level recorded was 140 t per hectare per year. This value increased to 174 t per hectare per year in 2011 but decreased to 168 t per hectare per year in 2021. The variations in potential soil loss are attributed to rainfall, as no management factors are considered in the estimation. The increase in potential soil loss from 2001 to 2011 was attributed to changes in rainfall patterns, such as increased intensity or duration of precipitation events. This would result in a higher erosive power of water and, consequently, higher potential soil erosion.

The application of potential soil loss estimation is relevant for tropical catchments like the Swat basin, where extensive deforestation has occurred due to logging activities, agriculture, and urbanization in recent years. Although the Universal Soil Loss Equation (USLE) was developed by the United States Department of Agriculture (USDA) for predicting erosion in the USA, it can also be applied to assess potential soil loss in areas if they remain uncultivated throughout the year. This applies to the Swat, where the conversion of forested areas to other land uses has increased the vulnerability to erosion. The absence of vegetation cover exacerbates the erosive impact of heavy tropical monsoon rains (Abdulkareem et al., 2019).

Correlation between soil erosion with different LULC changes

The lack of observed data to correlate projected model outputs and validation of erosion models is one of their main issues (Ganasri & Ramesh, 2016; Lazari et al., 2015). Additionally, the watershed's vast area makes conducting direct field measurements challenging, expensive, and time-consuming. As a result, the LULC change correlations corroborated the study's findings regarding soil erosion rates. This procedure overlapped the soil erosion maps (2001, 2011, and 2021) over the various land use class maps. In the present study, C factors ranged between 0 and 1. The value of C being 1 is associated with cleared land. Water bodies, snow, and urban environments are all categorized under C, which is 0, the lowest category. It is crucial to comprehend how various changes in LULC affect the spatial distribution of erosion classes. Because it will help policymakers and land use planners assess soil loss in its entirety

and identify appropriate responses. The LULC shift in Swat as a function of soil erosion content is illustrated in Fig. 10. Under all LULC situations (2001, 2011, and 2021), cleared land shows the highest erosion losses.

Bare land exhibited higher rates of extreme soil erosion, with percentages of 3.62%, 2.76%, and 2.53% in 2001, 2011, and 2021, respectively, emphasizing the vulnerability of this land cover type to erosion processes. Cleared land appears to have been more vulnerable to soil loss than other LULC types. The reasoning is that the cleared land surfaces will be more vulnerable to the high-energy rains typical of the area’s tropical monsoons. Because of this, soil particles are likely to become dislodged and carried away by the runoff process. L, S, K, and R factors are additional causes of severe soil erosion. The forest land cover class also experienced erosion impacts, with its relative size decreasing from 2001 to 2021. This reduction can be attributed to afforestation efforts, potentially linked to the Billion Tree Tsunami Project (BTTP). The presence of grassland areas, which offer protection against water erosion, has been observed to reduce the risk of severe erosion. This implies that improving vegetation cover can help convert higher erosion classes into lower classes. Analyses of the LULC in 2001, 2011, and 2021 have shown

Comparison with related studies

Due to the similarities in topography and rainfall patterns, the soil erosion rates obtained in this study align with the range of soil erosion rates reported by other researchers in neighboring areas. A comparison of average soil erosion rates from various studies conducted in Pakistan is presented in Table 7. The global soil erosion map revealed considerably higher values in comparison to the estimates presented in our study, which reported an average erosion rate of 21.32, 29.67, and 24.82 t ha⁻¹ year⁻¹. This disparity is particularly evident in cases where our study indicates erosion rates ranging from 0 to 1 t ha⁻¹ year⁻¹, whereas the global map reports significantly higher rates, averaging around 4 to 5 t ha⁻¹ year⁻¹ (Waseem et al., 2023). Furthermore, it is observed that the soil loss in Azad Jammu and Kashmir, Lower Dir, and in Chitral region is higher compared to our study area (Borrelli et al., 2017; Maqsoom et al., 2020; A. Khan & Atta-Ur-rahman, 2022). The analysis demonstrates that the soil erosion rates observed in the Rawal watershed (Ashraf et al., 2017) and Jhelum watershed (Aslam And Yoshimura, 2017) were lower than those reported in the present study. In contrast, the soil erosion map for Kashmir (Gilani et al., 2022) and the erosion map for the Jhelum watershed (Waseem et al., 2023) reported nearly identical soil erosion

Table 4 Actual soil loss from 2001 to 2021

Actual Soil loss (t ha ⁻¹ Y ⁻¹)	Soil loss ranges	2001 LULC classification		2011 LULC classification		2021 LULC classification	
		Area (km ²)	Area %	Area (km ²)	Area %	Area (km ²)	Area %
0–1	Very low	3604.97	67.26	3311.41	61.78	3501.36	65.32
1–5	Low	1154.92	21.55	1225.83	22.87	1106.48	20.64
5–10	Medium	404.57	7.55	577.38	10.77	506.90	9.46
10–50	High	149.17	2.78	131.69	2.46	153.67	2.87
> 50	Extreme	46.37	0.87	113.67	2.12	91.60	1.71

an increase in forest coverage and a decrease in agricultural and bare land areas over this period. Table 6 and Fig. 12 provide a detailed analysis of land use class-wise soil erosion for each individual class.

rates within this particular watershed. This can be attributed to the presence of rugged mountains, steep slopes, and a wetter climate characterized by frequent rainfall events.

Table 5 Potential soil loss from 2001–2021

Potential soil loss (t ha ⁻¹ Y ⁻¹)	Soil loss ranges	2001 LULC classification		2011 LULC classification		2021 LULC classification	
		Area (km ²)	Area %	Area (km ²)	Area %	Area (km ²)	Area %
0–1	Very low	3451.14	64.39	3123.06	58.27	3355.90	62.61
1–5	Low	1048.80	19.57	1317.38	24.58	1004.27	18.74
5–10	Medium	566.55	10.57	459.24	8.57	683.56	12.75
10–50	High	194.19	3.62	253.31	4.73	167.47	3.12
> 50	Extreme	99.31	1.85	207.00	3.86	148.79	2.78

Strengths and drawbacks

RUSLE is the best model available for estimating soil loss. This model is particularly useful for developing nations with limited data resources because of its ability to predict soil loss with minimal input. Complexity makes it hard to evaluate and validate the results of other models. Most other models have many opportunities for mistakes because they are based on empirical rules (Bezak et al., 2021). With this methodology, we can pinpoint problems that need immediate attention from upper management. It is a simple, flexible, and physical basis for estimating relative soil loss. Despite its many benefits, the RUSLE model does have certain drawbacks. We used regression analysis to create this equation with little field data on rainfall, soil, land cover, and landscape (Borrelli et al., 2021). Moreover, because this is based on the US data, its usefulness for a catchment in Pakistan is debatable. More long-term data is needed to calibrate and calculate the model's coefficients to utilize the model for location outside of the datasets on which it was calibrated. Soil loss, the controlling component in erosion, is typically not calculated, considering erosion in gullies or stream channels. Finally, considering only sediment deposition, routing, and sediment yield at the catchment outlet when estimating soil erosion leads to erroneous estimates; therefore, this method is not ideal (Li et al., 2023).

Conclusion

This study investigated the impact of land use and land cover (LULC) changes on soil erosion prediction in the mountainous District SWAT of Kpk, Pakistan, employing the Revised Universal Soil Loss Equation (RUSLE) model in conjunction with Geographic

Information System (GIS) techniques. By assessing key factors, including rainfall R , soil erodibility (K), slope length and steepness (L.S.), conservation practices (P), and land cover management C , the RUSLE model offered valuable insights into soil erosion dynamics. The integration of RUSLE with GIS proved to be an effective approach for tracking LULC changes. Notably, our analysis revealed significant shifts in LULC from 2001 to 2021, with the most prominent categories being grassland, bare area, cropland, natural trees, buildup area, water bodies, and snow. The expansion of natural tree cover, particularly the positive trend seen since 2001, suggests favorable changes in vegetation dynamics, likely influenced by initiatives such as the Billion Tree Tsunami Project (BTTP). Additionally, the buildup areas and snow cover showed increasing trends, reflecting shifts in human development and winter climate patterns. Conversely, the grassland and cropland areas decreased, indicating changes in land use. The study's results indicated significant variations in the mean soil loss across different periods. In 2001, the average soil loss was estimated at 21.32 t per hectare per year. This value increased to 29.67 t per hectare per year in 2011, suggesting an intensification of soil erosion processes. However, by 2021, the mean soil loss decreased to 24.82 t per hectare per year, indicating some improvement in soil conservation efforts or changes in land management practices. Our study sought to evaluate the impact of the Billion Tree Tsunami Project (BTTP) on soil erosion in the Swat region over the years 2001, 2011, and 2021. The observed reduction in soil loss in 2021 as compared to 2001 and 2011 suggests a positive influence of the BTTP on soil conservation efforts. This finding underscores the potential of afforestation initiatives in mitigating soil erosion and highlights the significance of environmental conservation programs in regions

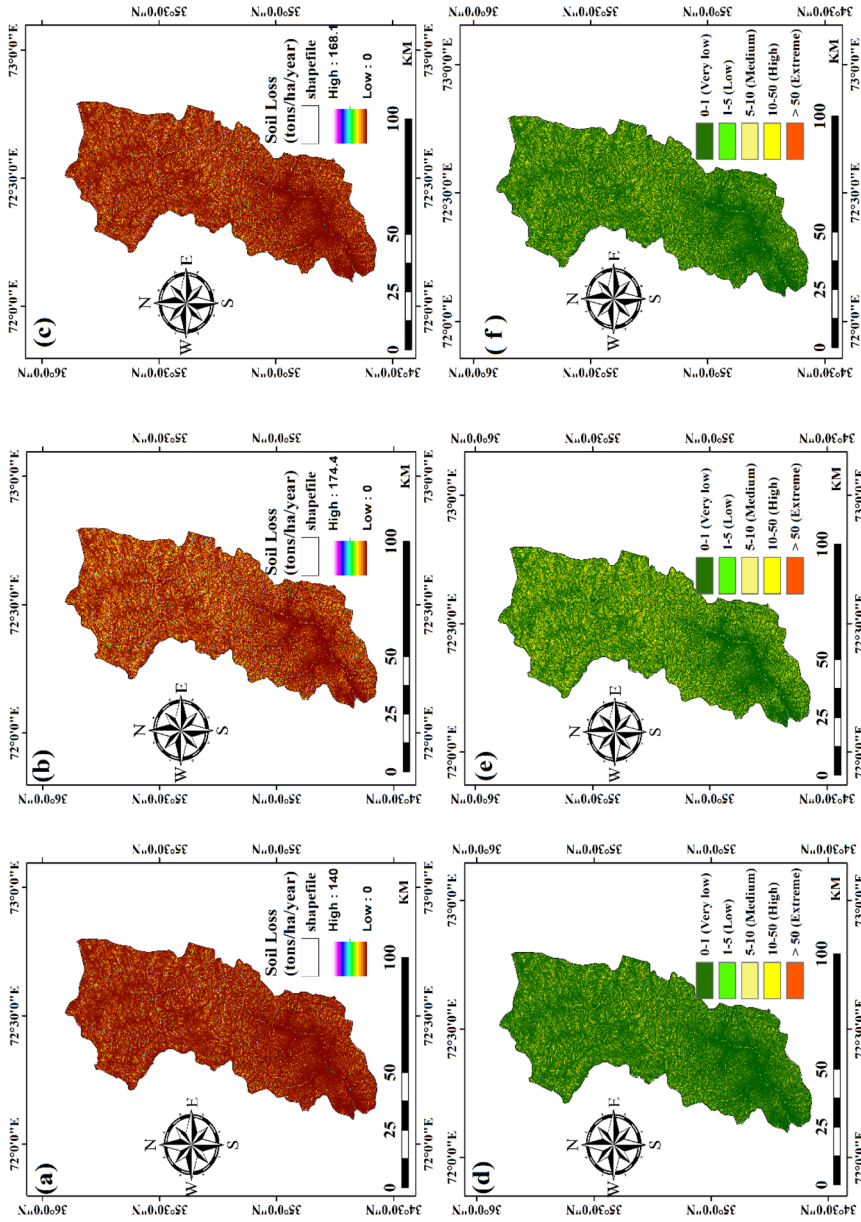


Fig. 11 Potential soil erosion and severity classes for the Swat District in 2001, 2011, and 2021. **a** Soil loss for 2001, **b** soil loss for 2011, **c** soil loss for 2021, **d** severity class for 2001, **e** severity class for 2011, and **f** severity class for 2021

Table 6 Land use class-wise soil erosion severity

LULC classes	Soil erosion year	% soil loss				
		Very low	Low	Medium	High	Extreme
Natural trees	2001	54.56	25.03	12.54	6.64	1.23
	2011	53.01	26.22	13.24	5.82	1.71
	2021	51.91	28.41	11.17	7.82	0.69
Grassland	2001	59.91	19.17	16.65	3.6	0.67
	2011	57.06	22.26	18.41	1.29	0.98
	2021	55.55	21.68	17.87	4.34	0.56
Water bodies	2001	61.77	34.04	2.01	2.14	0.04
	2011	65.46	32.23	1.54	0.74	0.03
	2021	58.93	37.65	1.45	1.92	0.05
Cropland	2001	51.36	21.06	15.65	9.06	2.87
	2011	53.71	26.45	14.76	3.73	1.35
	2021	48.32	27.87	16.98	5.27	1.56
Buildup area	2001	70.09	21.98	6.98	0.949	0.001
	2011	74.62	20.18	4.35	0.848	0.002
	2021	76.54	17.75	3.76	1.949	0.001
Snow	2001	80.15	16.65	2.44	0.758	0.002
	2011	82.22	14.98	1.99	0.799	0.011
	2021	80.84	15.86	2.65	0.649	0.001
Bare area	2001	32.65	34.87	16.75	12.11	3.62
	2011	34.8	32.07	19.57	10.8	2.76
	2021	34.38	29.46	18.75	14.88	2.53

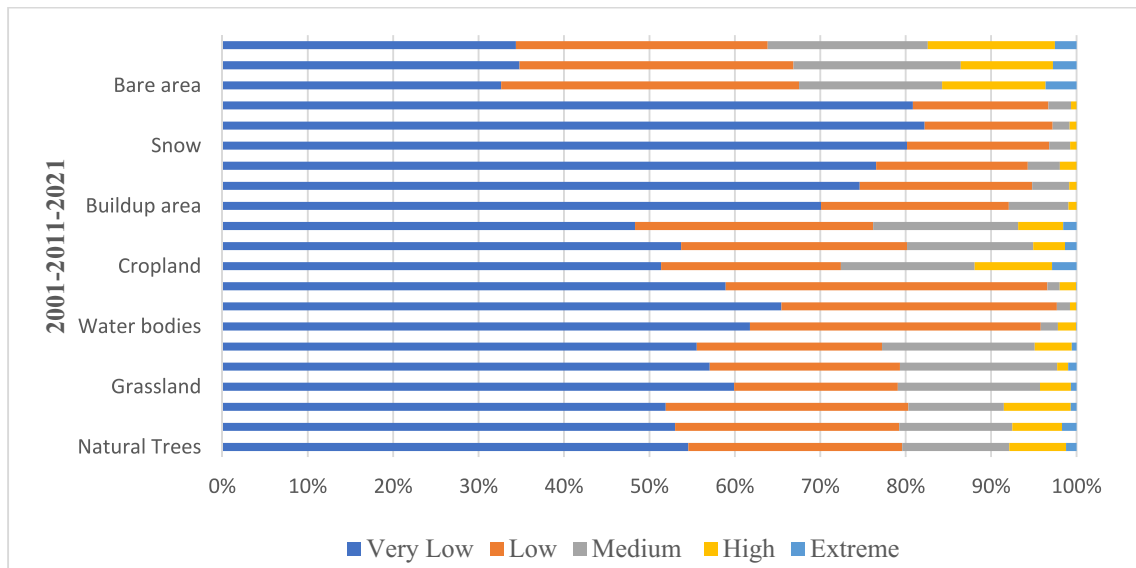


Fig. 12 Land use class-wise severity classes with a 10-year gap

Table 7 Comparison of soil loss estimation with local neighboring studies

Study region	Soil loss rate (t ha ⁻¹ yr ⁻¹)	Reference
Rawal watershed	10.3	(Ashraf et al., 2017)
Ghabbir watershed	22	(Ashraf et al., 2017)
Jhelum watershed	14	(Aslam And Yoshimura, 2017)
Jhelum watershed	17.51	(Aslam And Yoshimura, 2017)
Jhelum watershed	23.47	(Waseem et al., 2023)
Kashmir	40.88	(Borrelli et al., 2017)
Kashmir	22.25	(Gilani et al., 2022)
Chitral Region	78	(Maqsoom et al., 2020)
Potohar Region	148	(Batool et al., 2021)
Potohar Region	19	(Saleem Ullah et al., 2018)
Khyber Pakhtunkhwa	11.78	(Nasir et al., 2023)
Lower Dir	230	(A. Khan & Atta-Ur-rahman, 2022)
Swat (Pakistan)	21.32 (2001) 29.67 (2011) 24.82 (2021)	Current study

with vulnerable topography. However, we acknowledge the need for further research to delve deeper into the specific mechanisms driving these improvements and to consider potential confounding factors. As we move forward, it is imperative to continue monitoring and assessing the long-term sustainability and effectiveness of such projects in sustaining healthy ecosystems and preserving soil resources.

This study employed globally sourced spatial data products, including land cover, elevation, and soil maps, alongside an extensive review of relevant literature to estimate average values for key factors like soil erodibility and land cover management practices. Unfortunately, Pakistan faces challenges related to data scarcity, particularly at the national scale. While medium spatial resolution geospatial datasets are available for generating crucial products such as land cover and soil characteristics maps, they have not been produced or made publicly accessible on a national scale due to various obstacles including limited willingness, technological constraints, and financial limitations. It is important to note that the absence of ground-based soil erosion estimations prevented us from validating our results. However, despite these limitations, our research diligently utilized freely available geospatial datasets and adopted scientifically replicable methods and analysis techniques. The spatially explicit and temporal soil

erosion information generated in this study serves as a valuable resource for diverse applications, including soil conservation, land management strategies, and environmental impact assessments. Our findings contribute to the ongoing discourse on soil conservation, and we hope they inform future policy decisions and land management practices in the Swat Valley and similar regions. In conclusion, this research underscores the significance of considering LULC changes in soil erosion assessments and highlights the potential impact of afforestation initiatives on soil conservation in the region.

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Data availability Not applicable.

Declarations

Ethical approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors and are aware that with minor exceptions, no changes can be made to authorship once the paper is submitted.

Competing interests The authors declare no competing interests.

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