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Assessment of soil erosion in the Beas Valley, Kullu, Himachal Pradesh: A study of Western Himalayan landscape, Northern India

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Abstract

Soil erosion is a formidable global challenge with far-reaching consequences. It results in the depletion of soil nutrients, land degradation, decreased agricultural output, heightened runoff, and the exacerbation of geological hazards such as landslides and debris flows. This study focuses on the assessment of soil erosion in the Beas Valley region of Kullu, Himachal Pradesh, situated in the Western Himalaya landscape of Northern India. The research employs various datasets and a well-defined methodology to analyze the complex interactions between climate, soil, topography, and land use in order to understand and mitigate soil erosion risks. The primary data sources utilized in this study include rainfall data from the Climate Research Unit at the University of East Anglia, soil data from the Food and Agriculture Organization, Digital Elevation Model (DEM) data from the Shuttle Radar Topography Mission, and satellite imagery from Landsat. The research methodology is based on the Revised Universal Soil Loss Equation (RUSLE), a widely accepted model for assessing soil erosion. The RUSLE equation (A= R·K·LS·C·P) incorporates several factors to quantify soil erosion rates. The R-factor, derived from monthly and annual rainfall data, is used to estimate erosivity. The K-factor, determined using soil type and composition, characterizes soil erodibility. The LS-factor considers slope and flow accumulation, while the C-factor is calculated based on the Normalized Difference Vegetation Index (NDVI) from satellite imagery. Lastly, the P-factor accounts for the effectiveness of conservation practices. This interdisciplinary approach provides valuable insights into the dynamics of soil erosion in the Beas Valley region. By leveraging cutting-edge data sources, filed visit and a robust methodology, this study contributes to a better understanding of soil erosion processes in a fragile Himalaya ecosystem, facilitating informed land management decisions and environmental conservation efforts.

1. Introduction

According to the Food and Agriculture Organization's (FAO) Global Soil Partnership reports, nearly 75 billion tons of soil from productive agricultural lands are at high risk of erosion annually, resulting in estimated financial losses of $400 billion per year (Kayet et al., 2018). Asia faces a particularly daunting challenge, with approximately 663 million hectares affected by soil erosion, the highest among all continents (Rao et al., 2016). In India alone, soil loss is estimated at 1,559 Mg km^{-2} $year^{-1}$ (Reddy, 2003), with approximately 1,100 million hectares impacted by rainwater erosion and 550 million hectares affected by wind erosion (Dubey and Sharma, 2018; Kumar et al., 2022). This erosion significantly affects staple crop production, resulting in a GDP reduction of approximately 1.0%–1.7% and detrimental socioeconomic consequences (Lal, 2019; Dubey and Sharma, 2018). A previous report by Reddy (Reddy, 2003) revealed a loss of about 74 million tons of crucial soil nutrients due to erosion. These facts underscore the urgency of systematically assessing soil erosion to combat land degradation.

Soil erosion, a central component of land degradation, represents a formidable environmental hazard (Eswaran et al., 2001; Panagos et al., 2017; Poesen, 2018; Steinmetz et al., 2018). Land degradation has emerged as a major environmental challenge, particularly in developing countries where agriculture plays a dominant role (Krishna Bahadur, 2009; Xu et al., 2013; Rawat et al., 2016; Samanta et al., 2016; Saha et al., 2018).

In India, soil erosion caused by water stands out as a critical contributor to severe land degradation, exerting a significant impact on the topsoil and overall landscape. This concern is particularly pronounced in the Himalaya region (Mandal and Sharda, 2011; Bhattacharyya et al., 2015; Mahapatra et al., 2018).

The Himalayas, characterized by their diverse mountain ecosystems, grapple with extensive land degradation challenges, with soil erosion at the forefront (Chalise et al., 2019). Soil erosion is a pervasive issue in various climatic regions worldwide, including mountainous areas like the Himalayas (e.g., Garcia-Ruiz et al., 2015). Soil erosion in the Himalayas is driven by a complex interplay of natural processes and human activities (Jain et al., 2010; Prashanth et al., 2021, 2022). Therefore, assessing soil erosion in these ecologically sensitive Himalaya watersheds is essential not only for evaluating land degradation but also for promoting sustainable agricultural practices (Singh and Singh, 2018).

Oliveira et al. (2019) have highlighted that runoff from mountainous regions flowing towards lower elevations significantly accelerates erosion rates. Furthermore, frequent changes in land use patterns exacerbate runoff and lead to a loss of soil productivity, ultimately contributing to land degradation (Ang and Oeurng, 2018). As reported by Sharma (2008), a substantial portion of land degradation in the Himalaya region, amounting to 79%, is attributed to water erosion, primarily concentrated in river catchment areas. Notably, the lower Himalaya region is particularly susceptible to soil erosion, resulting in land degradation and rendering the land unproductive (Kaiser, 2004). In the state of Himachal Pradesh, located in the North Indian Himalayas, approximately 54% of the land is prone to soil erosion, with 98% of this erosion attributed to water-related factors (Kumar et al., 2014). The intricate and rugged terrain, tectonic pressures, and diverse climatic influences, coupled with human interventions, have further exacerbated the stress on natural resources, particularly land resources in the lower Himalayas (Prashanth et al., 2021). Therefore, under these challenging circumstances, it becomes imperative to accurately estimate soil loss, with a particular focus on areas experiencing land degradation. Such assessments are vital for sustainable planning and the effective conservation of natural resources in the Himalaya region (Yadav and Sidhu, 2010).

Efficient implementation of land and water conservation practices within a watershed necessitates a comprehensive assessment of soil loss resulting from water erosion and a precise understanding of its spatial distribution. Over the years, a plethora of empirical and physical models have been employed to predict soil loss caused by water erosion, including the Universal Soil Loss Equation (USLE: Park et al., 2011), the Revised Universal Soil Loss Equation (RUSLE: Tiwari et al., 2000; Ouyang et al., 2010), the Watershed Erosion Prediction Project (WEPP: Beasley et al., 1980), the Soil and Water Assessment Tool (SWAT: Gosain et al., 2009), the Areal Non-Point Source Watershed Environment Response Simulation (ANSWERS: Angima et al., 2003), the European Soil Erosion Model, Rule-Based Expert Systems, Hybrid Approaches, Sediment Concentration Graphs, Renard–Laursen Models, Unit Sediment Graphs, and Instantaneous Unit Sediment Graphs (24). While empirical models are widely favored for their reduced data input requirements, physical models rely on nonlinear partial differential equations to represent various hydrological processes, necessitating substantial data inputs (Abdelwahab et al., 2018).

Among these models, RUSLE has emerged as the most widely adopted empirical model for assessing soil erosion rates and losses. RUSLE calculates soil loss in relation to prevailing climatic conditions and various watershed features (Boufala et al., 2020). Multiple studies have assessed the performance of RUSLE in comparison to other models, consistently reporting statistically similar results (Tiwari et al., 2000; Mondal et al., 2016; Chen et al., 2019; Safwan et al., 2021). For instance, Tiwari et al. (2000) found comparable results between RUSLE and WEPP models, while Ubierna et al. (Tiwari et al., 2000) reported that the RUSLE model's soil loss estimates closely aligned with actual data. More recently, Safwan et al. (Safwan et al., 2021) confirmed a high degree of agreement between RUSLE and the WEPP model in predicting soil loss. Similarly, Mondal et al. (Mondal et al., 2016) reported that the RUSLE model closely matched actual soil loss data when compared to the USLE and modified Morgan-Morgan-Finney (MMF) models. Abdelwahab et al. (Abdelwahab et al., 2018) found RUSLE's soil loss results to be in close proximity to those obtained using SWAT and Agricultural Non-Point Source Pollution (AGNPS) models. Additionally, Boufala et al. (Boufala et al., 2020) confirmed a significant agreement in soil loss results between RUSLE and SWAT models. Consequently, the integration of the RUSLE model with Geographic Information Systems (GIS) presents a time-efficient and labor-effective approach for estimating erosion rates and soil loss over large areas.

In the present day, the combination of remote sensing and GIS techniques is increasingly employed for identifying regions vulnerable to water erosion and estimating soil loss. The joint use of hydrological models, remote sensing, and GIS holds tremendous potential for identifying erosion-prone hotspots, mapping the spatial distribution of erosion, and accurately estimating soil loss. Remote sensing and GIS applications have enabled the timely assessment of erosion across extensive landscapes. The utilization of a digital elevation model (DEM) is particularly valuable for extracting topographical features such as slope, flow direction, flow accumulation, and drainage networks, which are instrumental in assessing soil loss resulting from water erosion (Mondal et al., 2016). The integration of RUSLE with GIS offers a cost-effective solution that can be readily applied over large areas, enhancing consistency in soil loss estimation (Chen et al., 2019).

The amalgamation of RUSLE with GIS has found widespread application in previous studies (Renard et al., 1991; Sharma, 2010; Ranzi et al., 2012; Wijesundara et al., 2018; Thapa, 2020). For instance, Farhan et al. (Farhan et al., 2014) reported that 31.2% of the Wadi Kufranja watershed in Jordan was afflicted by severe erosion when employing RUSLE in conjunction with GIS. Similarly, Marondedze and Schütt (Marondedze and Schütt, 2020) found that 40% of the Epworth district in Zimbabwe suffered from severe soil erosion when employing the same approach. More recently, Amellah and Morabiti (Amellah and El Morabiti, 2021) utilized RUSLE in combination with remote sensing and GIS to identify erosion-prone zones and estimate soil loss in the Oued Laou basin in Morocco. Likewise, Srinivasan et al. (Srinivasan et al., 2021) applied RUSLE in tandem with GIS and reported erosion risk levels of 8.9%, 55.0%, and 35.0% for areas classified as severe, medium, and low erosion risk, respectively, within the Deccan Plateau in India. The correlation between actual soil loss and estimated soil loss by RUSLE was found to be robust (Pal and Chakrabortty, 2019a; Pal and Chakrabortty, 2019b).

Beyond the focused studies within the Beas Valley, several broader studies offer valuable insights for understanding soil erosion dynamics in the region. Kumar et al. (2019) leverage GIS and remote sensing to map soil erosion vulnerability across the entire Western Himalayas, encompassing parts of Himachal Pradesh, providing a regional context for the Beas Valley. Additionally, Sharma et al. (2015) delve into the impact of land use changes on soil erosion and sediment yield across Himalayan watersheds, offering insights directly applicable to the Beas Valley's unique land use patterns. Finally, Thapa et al. (2020) investigate the potential influence of climate change on soil erosion risk across the Himalayas, providing crucial context for future research efforts focused on mitigating erosion risks in the Beas Valley under changing climatic conditions. By considering these broader studies alongside focused research within the Beas Valley, researchers can gain a comprehensive understanding of the complex factors driving soil erosion in this ecologically sensitive region.

To address these pressing environmental challenges and to implement effective land and water conservation practices in the Beas Valley, a systematic assessment of soil erosion and its spatial distribution is of utmost importance. This study utilizes the integration of the Revised Universal Soil Loss Equation (RUSLE) with remote sensing and Geographic Information Systems (GIS) techniques to precisely estimate soil erosion and identify erosion-prone areas within the Beas Valley, Kullu, Himachal Pradesh, Western Himalaya Landscape, Northern India. This approach, as demonstrated in prior research, offers a cost-effective and efficient solution for large-scale soil erosion assessment, enabling policymakers to make informed decisions and address the critical issue of land degradation in this ecologically sensitive region.

2. Materials and methods

2.1. Brief description of Study area

The study area is situated within the Western Himalaya Beas River Basin, spanning approximately 31 kilometres from Katrain in north and Bhuntar in the south of Himachal Pradesh, India (Fig. 1). For analysis purposes, a 6 km buffer zone along the Beas River was defined. Geographically, it lies between latitudes 32°0' N to 32°20'0'' N and longitudes 77°50'' E to 77°15' E. The Kullu district is divided into five distinct geographic units based on the terrain's morphology: mountainous area, snow-covered area, denuded hills, valley area, and terrace area.

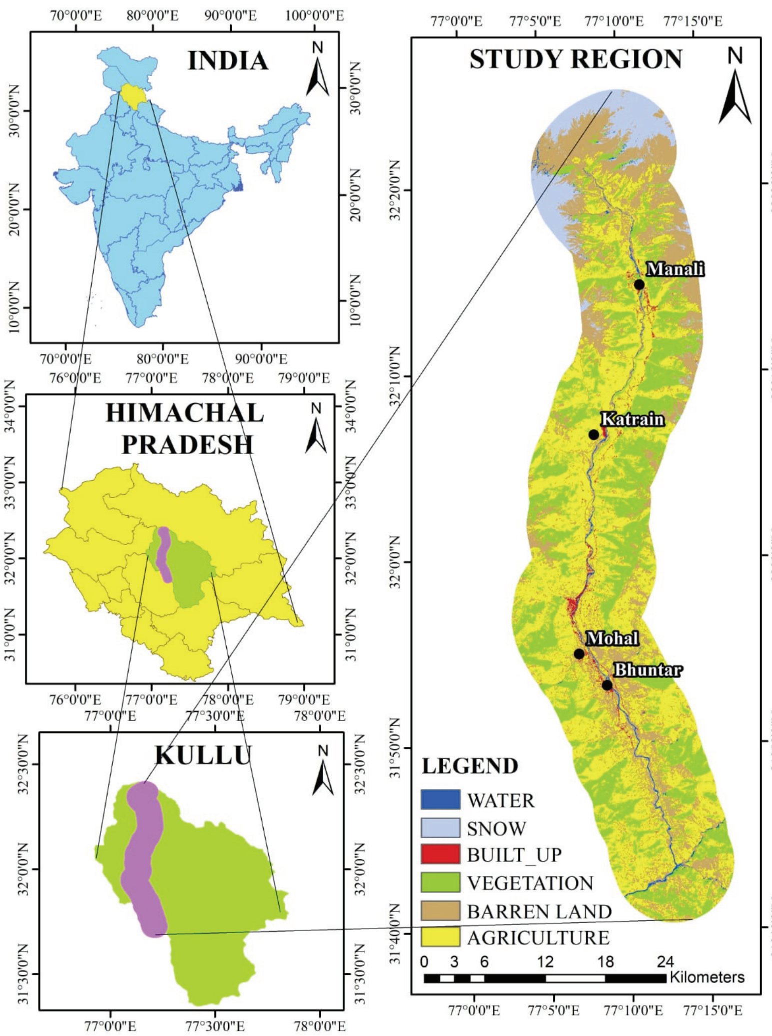

Fig. 1. Study area

The drainage system primarily consists of glacial and snow-fed perennial rivers, contributing to approximately 80% of the study area's hydrology (CGWB, 2013). With its higher altitude of 6,000 meters AMSL, the region spans from the temperate zone to the tundra zone. Within the research area, various litho-tectonic groups comprise rocks spanning from Precambrian to Quaternary periods (Shah and Mazari, 1998).

The geological classification of the Kullu district comprises two primary formations: porous and fissured. Fissured formations, originating from sedimentary, metamorphic, and igneous sources, vary from semi-consolidated to solidified deposits, thereby forming diverse hill ranges across the valley (Prasad et al., 2016). Human activities have notably impacted the region's landscape. Between 1961 and 2001, the population density of the study area surged by nearly 300%, from 28 to 69 individuals per square kilometer (Census, 2011). Comparison of land use data between 1994–95 and 2000–01 indicates a decline of around 6% in barren and non-agricultural land, while non-agricultural land use expanded by approximately 8% (Shah and Mazari, 2007). These trends reflect the growing influence of urbanization. The rising demand for groundwater due to population growth has led to a reduction in the shallow aquifer's water level (Bhatti, 2016).

2.2. Data set used

The issues associated with soil erosion and sediment transport have been longstanding challenges in the Beas Valley region of Kullu, Himachal Pradesh, and have been exacerbated by recent human interventions in the environment. To address these challenges, empirical models have proven to be valuable tools. However, the lack of critical data, such as sediment deposition information and high-frequency rainfall intensity records (less than 30 minutes), has limited the applicability of data-intensive models like USPED, WEPP, and the soil erosion module in the SWAT model within the study area.

Therefore, we have chosen to employ the Revised Universal Soil Loss Equation (RUSLE) model in our study of the Beas Valley region. RUSLE is particularly well-suited for this context, as it relies on input data that can be derived from remote sensing imagery, including essential information on land use, land cover, management practices, soil types, and their associated properties. Moreover, one of the key advantages of selecting the RUSLE model is its seamless integration with Geographic Information Systems (GIS), which greatly enhances the depth and quality of our erosion risk analysis within the Beas Valley region.

The primary objective of our study is to harness the power of the RUSLE model, combined with remote sensing and GIS techniques, to comprehensively assess erosion risk within Beas Valley region. Our methodology outlines the fundamental principles and procedures for estimating and predicting the parameters of the RUSLE model. These parameters are derived from a variety of data sources, including rainfall event records, Digital Elevation Models (DEM), soil type information, and land cover data. Our methodology paves the way for a robust analysis of erosion risk, offering valuable insights for effective environmental management and conservation efforts tailored to the unique characteristics of the Beas Valley region in Kullu, Himachal Pradesh.

The study utilized a comprehensive set of data sources to investigate annual soil erosion rate in the Beas Valley, Kullu, Himachal Pradesh, located in the Western Himalaya landscape of Northern India. These data sources are crucial for assessing the dynamics of soil erosion in this ecologically sensitive region.

The rainfall data were obtained from the Climate Research Unit at the University of East Anglia (CRU, UEA). This gridded time series dataset with a high spatial resolution of 0.50 for the year 2022 provides valuable information on precipitation patterns, which is essential for understanding the hydrological processes and their impact on soil erosion in the study area.

The soil data used in the study were sourced from the Food and Agriculture Organization (FAO). Specifically, the FAO-UNESCO Soil Map of the World at a scale of 1:5,000,000 was employed to characterize soil types and properties within the Beas Valley. This information is critical for assessing soil erosion vulnerability and understanding how different soil types contribute to erosion processes.

To analyze the topography of the study area, a Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) was utilized. This high-resolution DEM with a spatial resolution of 30 meters provides detailed elevation information, which is essential for modeling surface runoff and erosion potential.

Table 1.
Description of data source used in the study.

DATA	SOURCE	DESCRIPTION
RAINFALL DATA	CLIMATE RESEARCH UNIT, UNIVERSITY OF EAST ANGELIA (CRU,UEA) https://crudata.uea.ac.uk/cru/data/hrg/	A gridded time series dataset with 0.5^0 resolution for year 2023
SOIL DATA	FOOD AND AGRICULTURE ORGANIZATION (FAO) https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/	Soil Map at a scale of 1: 5,000,000
DIGITAL ELEVATION MODEL (DEM)	SHUTTLE RADAR TOPOGRAPHY MISSION (SRTM) https://dwtkns.com/srtm30m/	SRTM DEM of 30 m spatial resolution
SATALLIE IMAGE (LANDSAT DATA)	UNITED STATES GEOLOGICAL SURVEY (USGS) https://earthexplorer.usgs.gov/	LANDSAT 8-9 OLI/TIRS image (Path/Row-147/038) of 28/02/2023 with 30m resolution

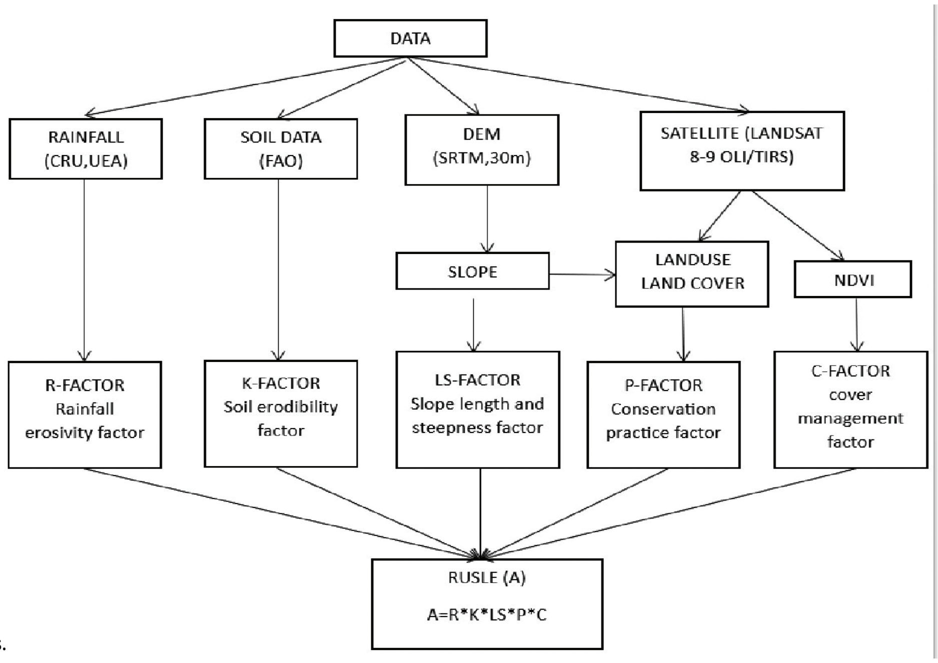

Fig. 2. Methodological workflow and data analysis.

Additionally, Landsat satellite imagery was acquired from the United States Geological Survey (USGS). Specifically, Landsat 8-9 Operational Land Imager (OLI)/Thermal Infrared Sensor (TIRS) imagery from October 28, 2022, was used. This satellite data with a spatial resolution of 30 meters allows for the analysis of land cover changes, vegetation dynamics, and their relationship with soil erosion in the study area.

2.3 Estimating parameters of revised universal Soil Loss Equation (RUSLE)

The estimation of parameters for the Revised Universal Soil Loss Equation (RUSLE) is a critical step in assessing average annual soil erosion rates (Sujatha and Sridhar, 2021). To derive the necessary input data for the RUSLE model, we employed various data mining techniques and harnessed machine learning algorithms, as detailed in prior studies (Ruidas et al., 2021; Ruidas et al., 2022a; Ruidas et al., 2022b; Ruidas et al., 2022c; Jaydhar et al., 2022). RUSLE integrates five key factors encompassing rainfall/precipitation, soil/land characteristics, topography/landscape features, land use and land cover (LULC) data, and conservation practices. This mathematical model is expressed as:

A= R*K*LS*C*P

where, A = average annual soil loss (t.ha^{-1} year^{-1}), R = rainfall erosivity index/factor (MJ.mm.ha^{-1}. h–1 year^{-1}), K = soil erodibility index/factor (t.ha.h.MJ^{-1} mm^{-1}), LS = slope length and steepness factor (−), C = crop/cover management factor (−), and p = support and conservation practices factor (−).

2.4 Rainfall Erosivity Index/Factor (R)

The Rainfall Erosivity Index, denoted as R factor, plays a pivotal role in assessing the intensity of rainfall and its direct impact on soil erosion within a given geographical area (Koirala et al., 2019). To compute the R factor, a continuous record of rainfall data is imperative, as it provides valuable insights into how the intensity of rainfall influences soil erosion, particularly water-induced erosion (Wischmeier and Smith, 1978). Extensive research has produced numerous equations for calculating the R factor (Kouli et al., 2009; Khosrokhani and Pradhan, 2014).

In this study, we adopt the R-FACTOR model developed by Wischmeier and Smith (1978) and Arnoldus (1980) to determine the Rainfall Erosivity Index. This parameter quantifies the erosive potential of raindrops, primarily due to their substantial impact force and kinetic energy (Nampak et al., 2018). It is widely acknowledged as the dominant force responsible for higher rates of soil erosion and soil loss (Fenta et al., 2016).

The R factor is mathematically expressed as:

$$R = \sum_{t=1}^{12} 1.735 * 10[1.5 * \log_{10}(P_1^2/P) - 0.08188]$$

Where: P_1 is monthly rainfall (mm)
P is annual rainfall (mm)

For our analysis, annual rainfall data was sourced from the Climate Research Unit (https://crudata.uea.ac.uk/cru/data/hrg/) at the University of East Anglia (CRU, UEA), which provides a gridded time series dataset with a resolution of 0.50 for the 2023 year (annually and monthly).

Notably, our findings reveal variations in the erosivity factor across the Beas River Valley in Kullu, Himachal Pradesh, India. The highest erosivity factor ranged from 111.54 in the north to 210.414 in the south for the year 2023, as illustrated in Fig. 3. These variations underscore the dynamic nature of rainfall erosivity within the region, emphasizing the need for accurate and localized assessments to guide soil erosion management strategies.

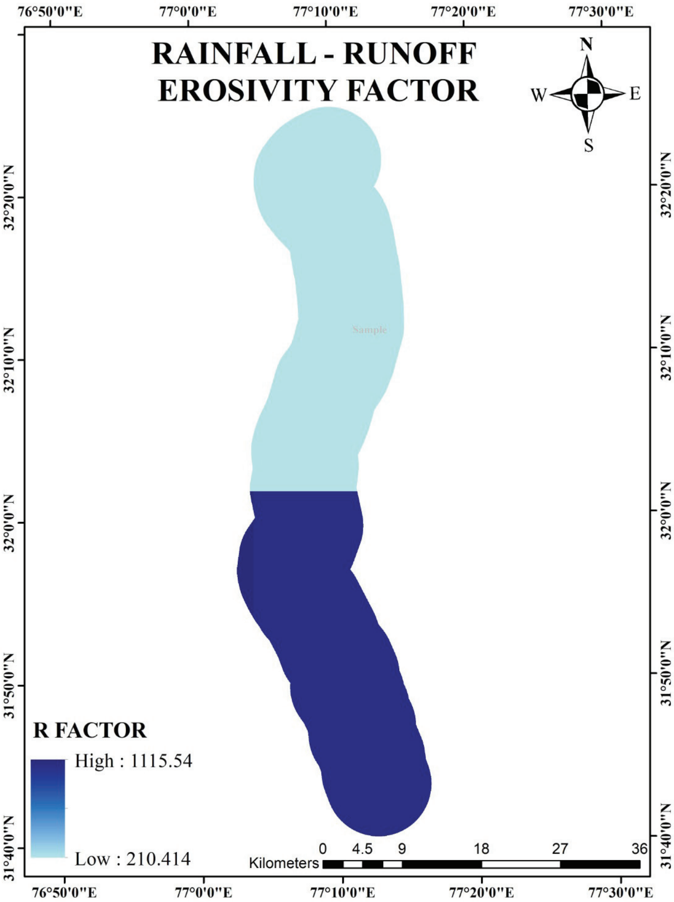

Fig. 3. Rainfall-Runoff Erosivity Factor Map

2.5. Soil Erodibility Index/Factor (K)

The Soil Erodibility Index, denoted as the K value, serves as a crucial indicator of a soil's susceptibility to erosion (Das et al., 2021). It primarily hinges on several key factors, including the soil's inherent characteristics, texture, organic matter content, and unsaturated hydraulic conductivity. The K value typically ranges from 0.0 to 1.0, with higher values indicating greater susceptibility to erosion. In this study, the K value was determined using soil data extracted from the Food and Agriculture Organization (FAO) soil map, which was obtained through GIS software.

The calculation of the K factor follows the methodology proposed by Williams (1995), which is expressed as:

Where:

$K = F_{csand} * F_{cl\text{-}si} * F_{orgc} * F_{hisand}$

$F_{csand} = (0.2+0.3*\exp[-0.256*m_s*(1-m_{silt}/100)])$

$F_{cl\text{-}si} = (m_{silt}/m_{silt} + m_c)^{0.3}$

$F_{orgc} = (1-0.25orgC/orgC+\exp[3.72-2.95*orgC])$

$F_{hisand} = \{1-0.7*(1-m_s/100)/(1-m_s/100)+\exp[-5.51+22.9(1-m_s/100)]\}$

Where:

m_s is sand percent of topsoil

m_{silt} is silt percent of topsoil

m_c is clay percent of topsoil

orgC is organic carbon percent of top soil

Table 2.
FAO soil type

FAO soil type	K-FACTOR
Bd29-3c	0.29
Be78-2c	0.38
GL	0.27

The Table 2 and Fig. 4 displays the calculated K factor values, which were subsequently scaled by multiplying by 0.1317 to bring them into the International System of Units (ISU) for easier interpretation (Ton Ha hr h/ha mj mm).

The results reveal a range of K factor values within the Beas Valley study area, varying from a low of 0.27 to a high of 0.38. These values are indicative of the soil's erodibility characteristics across the region, with higher K factor values implying greater susceptibility to erosion. This information is vital for assessing and managing soil erosion risk in the Beas Valley, particularly in areas where erosion control measures may be necessary to protect valuable soil resources.

2.6. Topographic Factor (LS)

The Topographic Factor, denoted as LS, serves as a combined indicator that characterizes the joint influence of slope

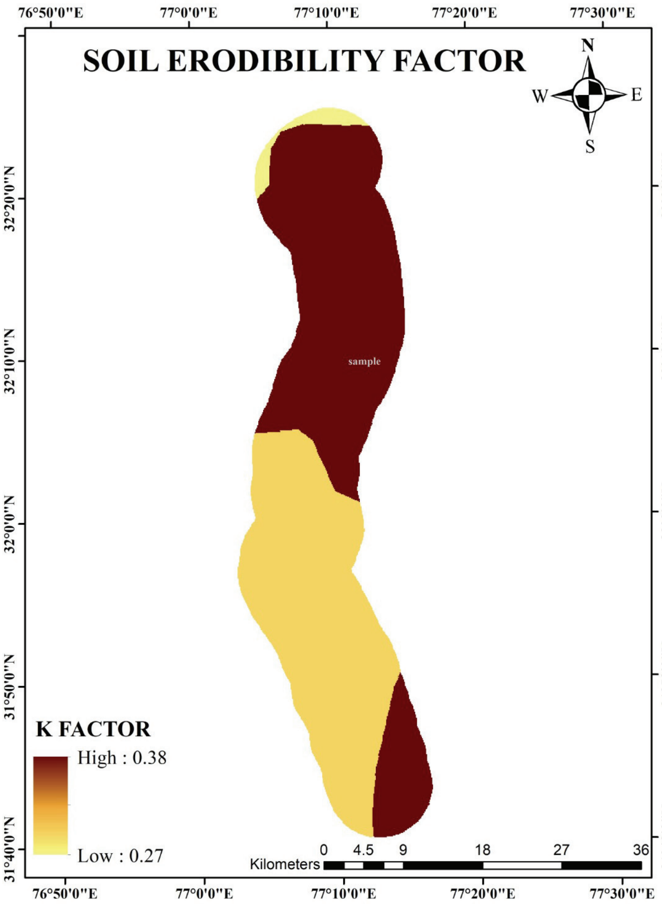

Fig. 4. Soil Erodibility Factor Map

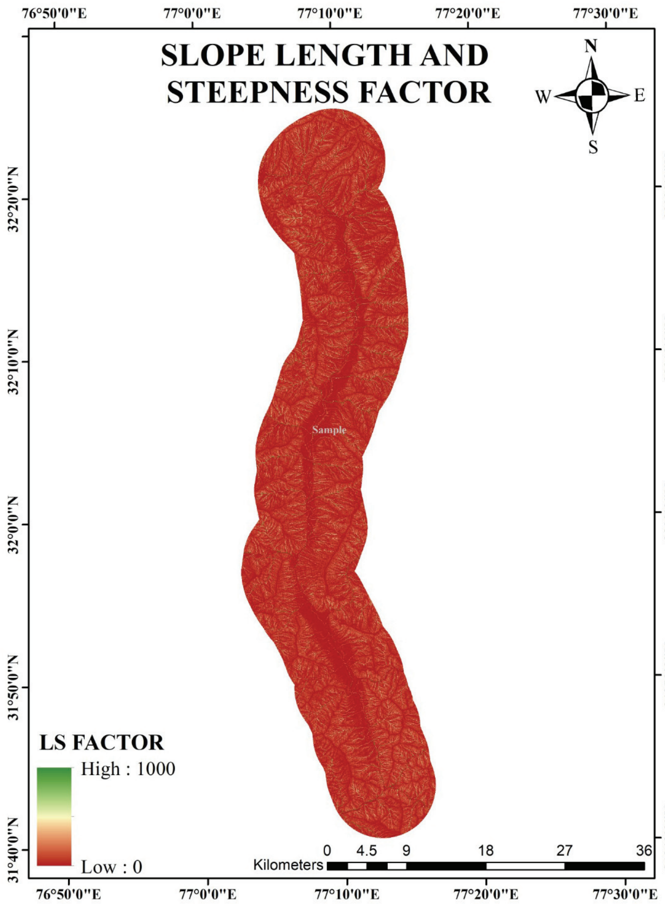

Fig. 5. Topographic Factor (LS) Map

length (L) and slope steepness (S) on the rate of soil erosion or soil loss (Amsalu and Mengaw, 2014). In this study, the LS factor was assessed utilizing a „flow accumulation" raster dataset, which contains information on the cumulative number of pixels contributing to the flow into a specific cell. The computation of the LS factor involved the use of a „flow direction matrix" that dictates the natural drainage paths for all cells within a Digital Elevation Model (DEM).

The LS factor was determined by considering the flow accumulation matrix, pixel size, and pixel slope, employing a raster calculator within a GIS-based environment. The calculation equation, as reported by Panagos et al. (Panagos et al., 2015), is presented below:

$$LS = (\text{flow accumulation}*\text{cell size}/22.13)^{0.4} * (\sin \text{of slope}/0.0896)^{1.3}$$

$$\text{Sin of slope} = \sin(\text{slope} * 0.017533)$$

Where:
- The „flow accumulation" is the cumulative number of pixels contributing to flow into a specific cell.
- The „cell size" represents the size of each pixel.
- The „slope" denotes the slope of the terrain.

It's noteworthy that the Beas Valley in Kullu exhibits a wide elevation range (Fig. 2), spanning from 1,000 to 6,000 meters above sea level. This topographic diversity is characterized by deeply incised river valleys interspersed with towering mountain ridges and glacier-capped peaks (Prasad et al., 2016).

The LS factor values within the watershed area exhibit considerable variability, ranging from low values of 0 to high values of 100. These values reflect the combined effects of slope length and steepness on soil erosion potential within the Beas Valley, highlighting areas where erosion control measures may be particularly important to mitigate soil loss.

2.7. Cover/Crop Management Factor (C)

The crop management factor (C factor), often referred to as the cover management factor, plays a pivotal role in assessing the impact of cropping and related practices on soil erosion (Chalise et al., 2019; Sandeep et al., 2021). It provides insights into how vegetative cover responds to water erosion, making it a valuable indicator of erosion susceptibility. Regions lacking protective vegetative cover are more susceptible to high water erosion rates, while areas shielded by vegetation experience lower soil erosion rates. Nearing et al. (2004) emphasized the sensitivity of the C factor to spatiotemporal variations, highlighting its dependency on factors like vegetative growth and rainfall conditions.

The C factor is quantified as the erosion-weighted ratio of soil loss from land under crops or vegetative cover to the corresponding loss from bare fallow or unprotected soil surfaces

(Wischmeier and Smith, 1978). This factor is dimensionless, with values ranging from 0 to 1. A value of 0 indicates an area with sufficient vegetative cover, well-protected from erosion, while a value of 1 signifies a barren, uncovered area highly susceptible to soil erosion. Notably, robust vegetative cover shields against soil erosion by reducing runoff intensity and minimizing the impact of raindrops on the soil surface (Ranzi et al., 2012). Consequently, the presence of vegetative cover, along with topography, significantly influences the rate of soil loss (Zhou et al., 2008; Li et al., 2019).

The calculation of the C factor follows the methodology proposed by Durgion (2014), which is expressed as:

$$C = (-NDVI + 1) / 2$$

Where:
- NDVI is the Normalized Difference Vegetation Index.
- NIR is the Near-Infrared band.
- RED is the Red band.

The vegetative cover factor (C) for the year 2023 was calculated using the provided equation (Fig. 6).

The NDVI values for that year ranged from Low −0.23 to 0.56, respectively. The resulting C factor values indicated higher erosion susceptibility in barren land areas, while lower values corresponded to regions with significant vegetative cover.

2.8. Conservation Practice Factor (P Factor)

The conservation practice factor, denoted as the P factor, serves as a key indicator of the positive influence of soil and water conservation practices on mitigating soil erosion within agricultural contexts. Wischmeier and Smith (1978) conceptualized the P factor as the percentage reduction in erosion achieved under conservation and protective conditions when compared to typical erosion scenarios. P factor values are expressed on a scale between 0 and 1, where values nearing 0 signify that the area benefits from effective soil and water conservation practices. Conversely, values closer to 1 suggest a lack of appropriate conservation measures (Table 3).

In this study, the P factor map was developed by utilizing pre-existing P factor values corresponding to relevant land-cover classes, which were sourced from established literature (Wischmeier and Smith, 1978; Wanielista and Yousef, 1993; Londhe et al., 2010).

This factor plays a critical role in assessing the impact of various conservation practices, such as contour farming, strip cropping, and bunding, on soil erosion rates. It is represented as the ratio of soil loss from a piece of land where specific conservation practices are implemented to the equivalent soil loss from the same land in the absence of these conservation measures.

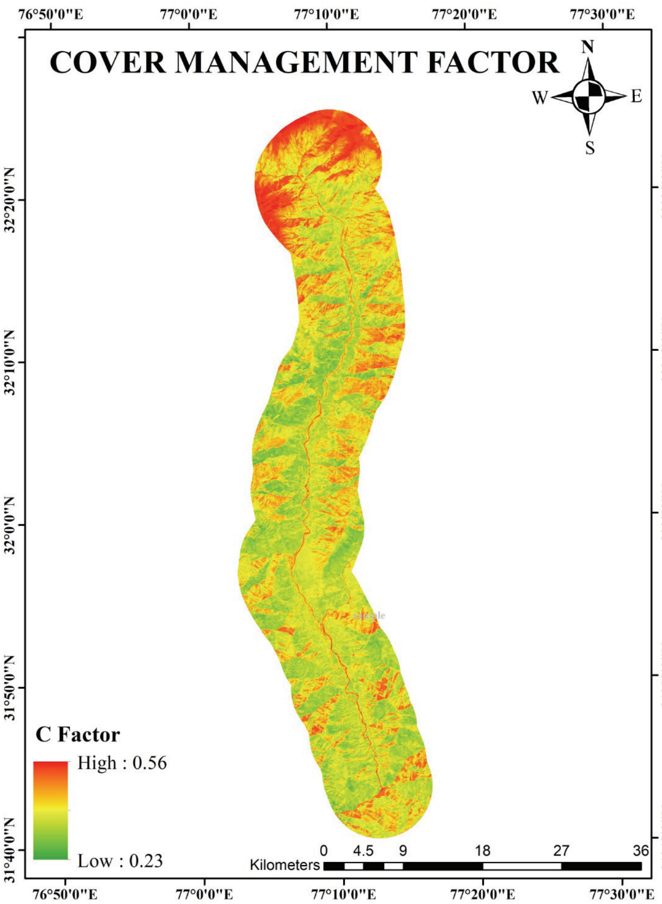

Fig. 6. Cover/Crop Management Factor (C)

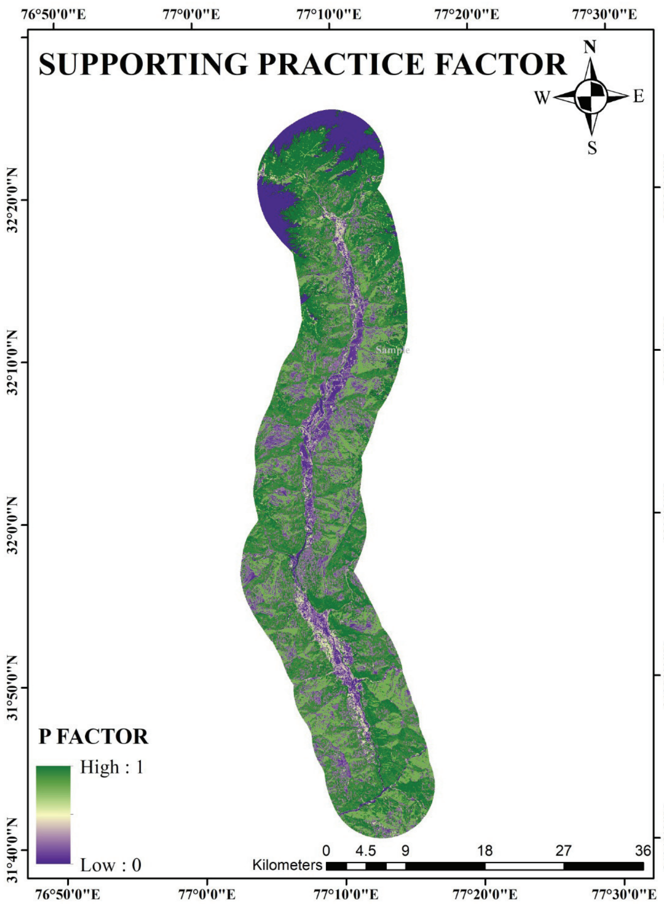

Fig. 7. Conservation Practice Factor

3. Result

The Beas River Basin in Kullu, Himachal Pradesh, faces a serious threat from soil erosion, impacting its environment and agricultural sustainability.

This study analyzes the potential for soil loss, categorized by annual soil loss per hectare (t/ha/yr). Areas with minimal erosion (0–50 t/ha/yr) benefit from existing conservation measures, while moderate erosion (50–100 t/ha/yr) requires improvement. Significant (100–250 t/ha/yr) and high erosion (250–500 t/ha/yr) zones demand immediate attention and erosion control measures. Very high (500–1000 t/ha/yr) and extremely high erosion (1000–2000 t/ha/yr) areas require urgent action to protect soil fertility and prevent land degradation. Exceptionally severe (2000–5000 t/ha/yr) and critical erosion (5000–10000 t/ha/yr) necessitate comprehensive interventions to avoid environmental disaster. Finally, areas exceeding 10,000 t/ha/yr face a crisis demanding extraordinary efforts to prevent irreversible damage. Land use significantly influences this issue, with an average loss of 19.9 t/ha/yr in 2023. Conservation and land management strategies must prioritize areas based on their erosion category, with lower erosion zones requiring maintenance and higher erosion zones needing urgent and intensive action. Maintaining this balance is crucial for the Beas River Basin's well-being and long-term sustainability.

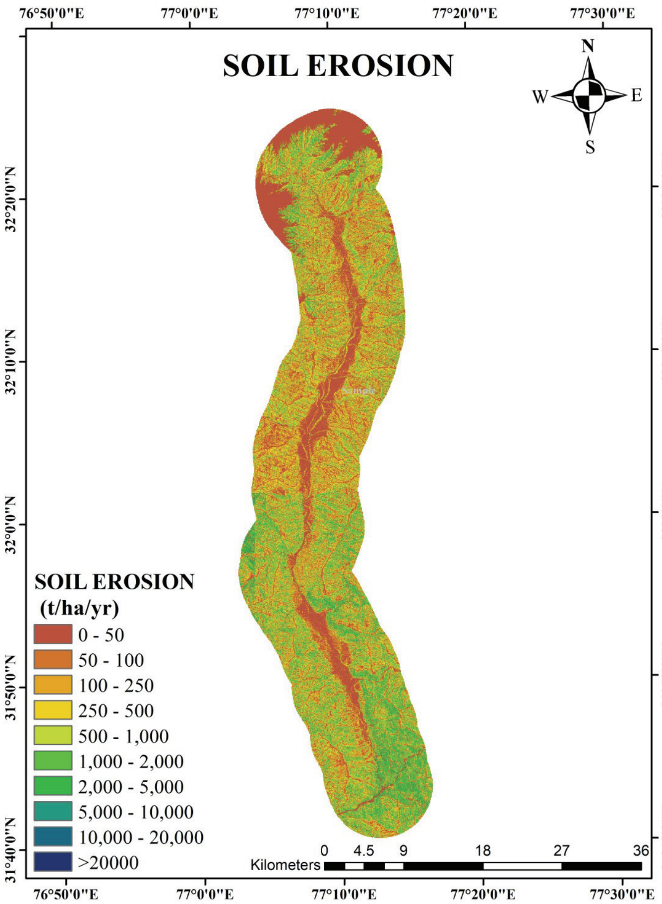

Fig. 8. Annual soil erosion estimation

The potential for soil erosion in the Beas River Basin of Kullu, Himachal Pradesh, is a critical factor that impacts the region's environmental health and agricultural sustainability. This potential soil erosion, denoted as A and measured in tons per hectare per year (t/ha/yr), varies across different zones, each presenting unique challenges and implications.

4. Discussion

The analysis of the soil loss potential classes in the Beas Valley, Kullu, Himachal Pradesh for the year 2023 reveals several important insights (Table 3).

Table 3.
Area (in percent) under different soil loss potential class

Area in percentage of 2023 year	
Soil loss class	%
0–500	66.08
500–2000	28.10
2000–5000	4.91
5000–10000	0.70
>10000	0.18

Table 4.
land use and land cover (LULC) classes in the Beas Valley, Kullu, Himachal Pradesh

LULC classes	Area (in percentage) of different soil loss potential classes in 2023 year				
	Very low (0–500)	Low (500–2000)	Moderate (2000–5000)	High (5000–10000)	Very high (>10000)
Water	100	0	0	0	0
Agriculture	67.67	25.43	5.06	1.42	0.42
Vegetation	62.89	30.44	4.84	1.4	0.43
Barren land	56.03	35.17	7.13	1.35	0.32
Built-up	100	0	0	0	0
snow	99.84	0	0.16	0	0

While most of the Beas Valley enjoys low soil loss (66%), a concerning 28% experiences moderate risk. Even pockets of high and very high risk exist, demanding immediate attention. This distribution highlights the need for targeted conservation efforts. Low-risk areas, primarily covered by forests and grasslands, require maintenance of current practices. However, moderate-risk zones, often characterized by shrublands and croplands, necessitate improved measures like cover cropping and terracing. The critical zones lie in the high and very high risk categories, encompassing barren land and built-up areas. These require urgent action like intensive a forestation and erosion control structures to prevent irreversible damage. This analysis underscores the crucial link between land use and soil erosion. Prioritizing conservation based on risk levels is essential for the Beas Valley's long-term sustainability.

The Beas Valley's soil loss story unfolds across its diverse landscapes (Table 4). While water bodies enjoy natural protection with minimal erosion risk (0–500 t/ha/yr), agriculture demands attention. Most agricultural land experiences low to moderate risk (0–500 t/ha/yr and 500–2000 t/ha/yr), but a significant portion faces moderate risk, highlighting the need for erosion control measures to ensure sustainable harvests. Similarly, vegetation, crucial for erosion mitigation, reflects this mix. While most enjoys low risk (0–500 t/ha/yr), some areas show slightly higher potential (500–2000 t/ha/yr). Interestingly, barren land and built-up areas primarily fall into low to moderate categories, suggesting their limited overall impact compared to agriculture and vegetation. Finally, snow-covered regions showcase minimal risk (0–500 t/ha/yr), reflecting their stable winter conditions. This analysis emphasizes the importance of land cover in understanding soil erosion risks. Tailored conservation measures are crucial across the valley, from mitigating moderate risks in agriculture to protecting vulnerable vegetated areas and ensuring sustainable land management practices across all landscapes.

5. Conclusion

In conclusion, the outcomes of this study have underscored the significant influence of land use on soil erosion in the Beas Valley, with an average soil loss of 19.9 t/ha/yr recorded for the year 2023. Through a comprehensive analysis of land use and land cover changes, we have observed the dynamic interplay of water bodies, agriculture, vegetation, barren land, urban development, and snow cover, all of which play crucial roles in shaping soil erosion patterns in the region. Moreover, the integration of the Revised Universal Soil Loss Equation (RUSLE) model with remote sensing and GIS techniques has allowed us to estimate parameters essential for assessing soil erosion risks. The calculation of rainfall erosivity (R-factor), soil erodibility (K-factor), topographic (LS) factor, and conservation practices (C-factor and P-factor) has provided valuable insights into the potential for soil loss and the effectiveness of conservation measures. Our findings have identified critical zones with varying degrees of soil erosion risk, ranging from low to extremely high potential. This knowledge is instrumental in formulating targeted conservation and land management strategies, tailored to the specific needs of each area. It is imperative that regions with higher erosion potential receive immediate attention and intensive measures to safeguard soil health, preserve the environment, and ensure agricultural sustainability. Looking ahead, the preservation of this delicate balance is essential for the well-being of the Beas Valley in Kullu, Himachal Pradesh. As we move forward, this research serves as a valuable resource for policymakers, land managers, and environmentalists, providing guidance for sustainable practices and the preservation of the region's natural beauty. It is our hope that these findings will inspire collaborative efforts to protect and nurture this ecologically vital region, ensuring its prosperity for generations to come.

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