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Spatial Estimation of Soil Erosion in Quetta Region, Pakistan: A GIS and Remote Sensing Integrated RUSLE Model-Based Approach

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ABSTRACT

Soil erosion is a prevalent issue causing land degradation worldwide. This study aims to determine the spatial distribution of annual soil erosion through the utilization of the Revised Universal Soil Loss Equation (RUSLE) model in Quetta sub-basin, situated in the southwestern region of Pakistan. To accomplish this, numerous data mining techniques were employed, along with machine learning algorithms, to produce thematic layers (R, K, LS, C, and P) that served as input parameters for the RUSLE model. According to the resultant model, soil erosion in the study area ranged from 0.00 to 866 tons per hectare per year. The estimated values for rainfall-runoff erosivity (R), soil erodibility (K), topography (LS), and cover management (C), factors ranged from 147 to 191 ($MJ.mm.ha^{-1}.h^{-1}year^{-1}$), 0.0229 to 0.0259 ($t.ha.MJ^{-1}mm^{-1}$), 0.002 to 360.77, and 0.001 to 1, respectively. The statistics revealed that 58% of the land in the study area experiences a very low degree of soil erosion, with an erosion rate of less than 13.58 t/ha/year. About 24% of the study area faces low erosion, with an erosion rate spanning from 13.58-44.16 t/ha/year. 13% of the area is demarcated as moderate soil erosion severity, at an erosion rate ranging from 44.16-81.53.14 t/ha/year. On the other hand, 5% of the study area experienced high to very high soil erosion, with an erosion rate of 81.53-866.34 t/ha/year. The northern part (Takatu range), north-eastern part (Zarghoon range) eastern-central (Murdar range), and western-southern (Chiltan range), which are characterized by steep slopes and barren land, experience high to very high severity of soil erosion. Decisively Remote Sensing and GIS, in combination with the RUSLE model, are significant for identifying input factors for modeling soil erosion and resource management. This study will provide firsthand guidance to assist policy/decision-makers and planners in pinpointing the erosion-prone areas that urgently need soil conservation measures.

Keywords: Soil erosion, RUSLE model, GIS, Geospatial data, Quetta sub-basin

INTRODUCTION

Soil erosion is a pressing geo-environmental concern that poses a significant threat to the agricultural sector on a global scale (Robinson *et al*., 2017). Soil erosion also referred to as land degradation, is a major problem that can lead to a range of critical issues. It can have a distressing impact on the ecosystem and the biodiversity it supports (Panagos *et al*., 2016). The land degradation has emerged as a momentous threat worldwide, impacting over 2.6 billion people across more than 100 countries. In developing countries, climate change and anthropogenic activities have fueled the rate of land degradation (Kebede *et al*., 2021; Singh *et al*., 2023). The process of erosion is influenced by a multitude of biophysical and environmental factors, which can interact with each other in complex ways. It is often linked to unsustainable human practices such as deforestation and intensive agriculture. The intricate interplay between land usage, topography, rainfall intensity, and soil types are the root causes of soil erosion (Bayati, 2016; Kayet *et al*., 2018).Previous studies have identified soil erosion as a critical factor leading to the loss of topsoil and degradation of farmland (Dutta *et al*., 2015; Qin *et al*., 2018; Shit e*t al*., 2015). Furthermore, it has been discovered in several studies (Gelagay & Minale, 2016; Panditharathne *et al*., 2019; Ullah *et al*., 2023) that the erosion can transport harmful materials downstream and contaminate water bodies. Overall, soil erosion has negative effects on the environment through depleting soil nutrients, water quality deterioration and agricultural productions, resulting in economic costs and human casualties. Evaluating and mapping soil erosion helps identify areas for implementing control measures and mitigation practices.

Over the years, there has been increasing concern about the state of soil resources worldwide, leading to a surge in global interest in the preservation and restoration of this vital resource. As a result, various initiatives and efforts have been put in place to ensure the sustainable use of soil and promote its health and productivity. To better understand and predict the severity of soil loss/erosion over time, various models have been adopted. Some of these widely used soil erosion prediction models include, Water Erosion Prediction Project (WEPP), Universal Soil Loss Equation (USLE), Modified Universal Soil Loss Equation (MUSLE), Revised Universal Soil Loss Equation (RUSLE), European Soil Erosion Model (EUROSEM), Agricultural Nonpoint Source model (AGNPS), and the Erosion Productivity Impact Calculator (EPIC). The selection and implementation of a suitable soil erosion model is reliant upon several factors, namely; the availability of data, and the spatial and temporal scales of the application of model. The choice of model should be carefully considered with due regard to the size of the selected area, and the duration of the study period. Many other factors such as soil characteristics, land use, and climate must also be taken into account when choosing the most appropriate model. By cautiously assessing these factors, the desired level of accuracy and effectiveness can be attained in the results. Among these models/equations, RUSLE is the most commonly used as it is capable of accurately calculating annual soil loss and can be easily integrated with both ArcGIS environment and satellite data. This makes it a powerful tool for predicting and managing soil erosion in various regions (Fiener *et al*., 2020; Ghosal & Das-Bhattacharya, 2020).

In Pakistan, agriculture has been the backbone, but wind and water erosion affect more than 76% of the land, encompassing approximately 16 million hectares and resulting in the loss of around 1 billion tons of fertile soil annually (Pimentel & Burgess, 2013). This poses a risk to both the livestock sector and ecological stability, and it also jeopardizes the potential for sustainable economic growth (Anjum *et al*., 2010; Gilani *et al*., 2022). Even though RUSLE is widely used for estimating and mapping soil erosion around the world, its use in Pakistan has been limited. A very few studies have been conducted in the northern part of the country (Nasir *et al*., 2006); Abuzar, 2012; Ashraf *et al*., 2017; Abuzar *et al*., 2018; Ullah *et al*., 2018; Ashraf, 2020. There is a significant research and knowledge gap concerns to research findings on soil erosion in mountainous regions at basin level. There are no scientific based findings available on soil erosion in southern part of the country. In study area, estimation and measuring the soil erosion is challenging due to factors like lack of field data availability, difficult terrain, and biodiversity. In such restricted conditioned area geospatial technology provide a cost-effective tool to portray this environmental issue. The present study is an attempt to utilize geospatial technology for estimation of spatial distribution of soil erosion in south-western part of the country. The main objective of the current research is to utilize the RUSLE model, geospatial data, and GIS tools to estimate the annual soil erosion in Quetta sub-basin, Pakistan. The study aims to apply the RUSLE model, scrutinize the relevant erosion factors and determine the rate of soil erosion in the study area to evaluate the extent and severity of soil erosion rate within specified region.

MATERIALS AND METHODS

Study area description

The study area of Quetta sub-basin is part of the Pishin River Basin, falls within the geographic coordinates of 29°45`00"N to 30°30`00"N latitude and 66°45`00 to 67°20'00 E longitude (**Figure 1**). Based on climatic standpoint, the Quetta Sub-basin can be found in the upper highlands region and experiences semi-arid conditions. Its climate is classified as "sub-tropical continental highland," with mild to hot summers and harsh winters. The winter season lasts from October to March, with an average temperature of 3-5ºC. The spring season occurs during April and May and has a temperature of around 15ºC. The Summer spans from May to September, with temperatures ranging from 24-27ºC, while autumn takes place from September to November and has an average temperature of 12ºC.The study area has varied topography, including mountain ridges, depressions, and small plains. The sub-basin height raises towards the northeast of Quetta Valley, where the Zarghoon range is located, the highest peak in the area (3570m asl). The Takatu, Chiltan and Murdar Ghar ranges are also exposed in the north, west, and east respectively. The central part is largely flat, sloping gently southward. The average topographic elevation of the study area is 1650m asl (Ali & Aftab, 2022).

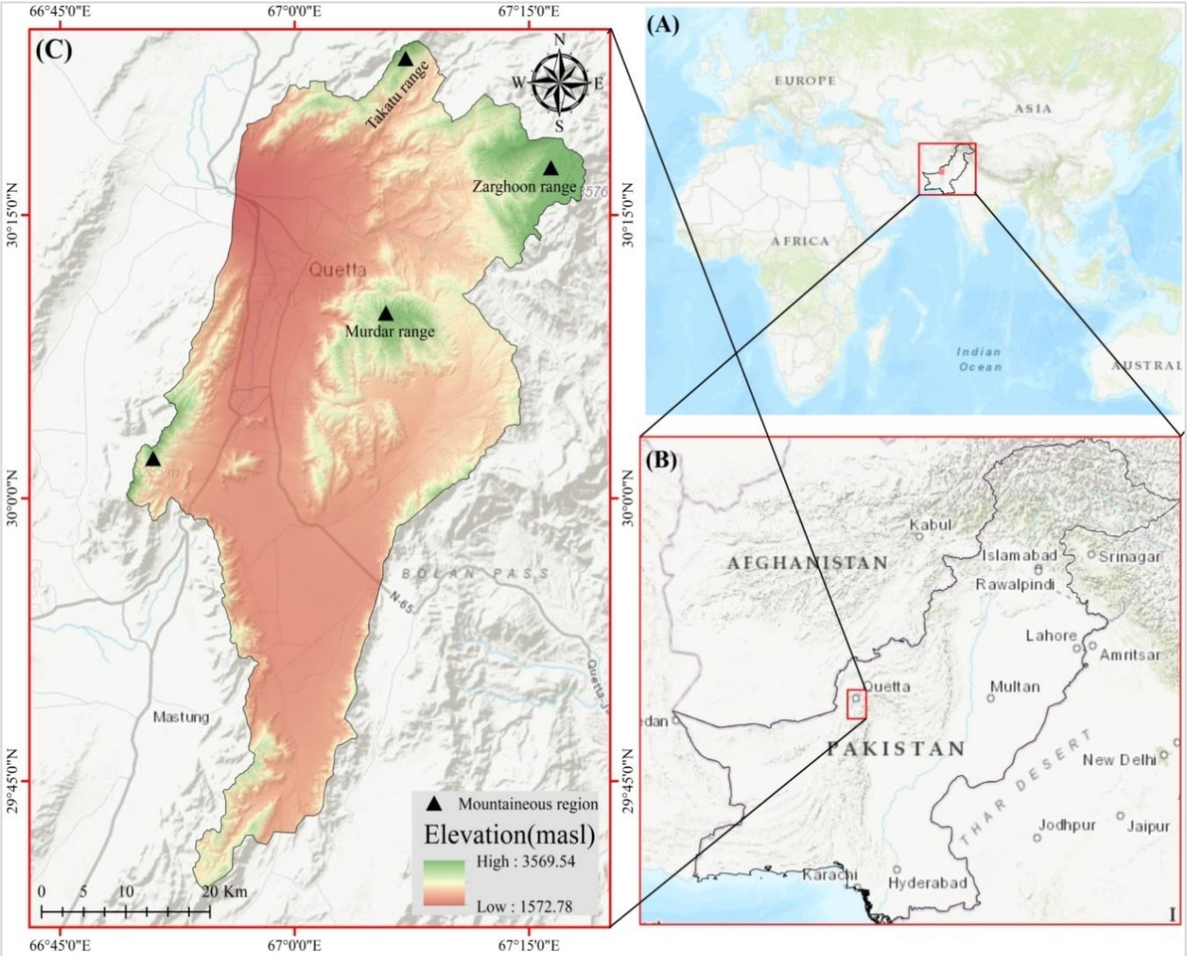

Figure 1. Location map of (A) World map (B) Country map (C) Study area (Quetta sub-basin) (**Source:** Ali *et al*., 2024).

In current research, the methodology used is portrayed in **Figure 2**. Additionally, **Table 1** provides an overview of the various datasets utilized in the study and their corresponding sources. The initial stage involved the generation of a geospatial database containing all the necessary datasets for the RUSLE equation/model. These datasets were collected using a combination of geospatial techniques and machine learning algorithms to create thematic layers (R, K, LS, C, and P), which served as the input parameters for the RUSLE model. Subsequently, in the second stage, all acquired data was preprocessed, and thematic layers were generated from remote sense data within the ArcGIS environment. Geographic Information System (GIS) was the primary tool applied in the processing stage. Finally, in the last stage, the "Raster calculator" was used to overlay all thematic layers in order to produce the annual soil erosion map.

Datasets types and acquisition sources

Acquisition of data is the most important and critical step in research. ALOS PALSAR DEM 12.5m resolution was downloaded from Alaska official website (https://asf.alaska.edu). The precipitation data for the last 23 years (2000-2023) was acquired from the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS). LULC was downloaded from ESRI living atlas website. Soil related data was acquired from Harmonized World Soil Database (HWSD) v2.0 and SoilGrids 2.0.The estimation of all parameters related to RUSLE model are describe in proceeding sections.

This study targets to apply the RUSLE equation/model to examine the relevant erosion factors and determine the average rate of soil loss in the study area to evaluate the extent and severity of soil erosion in the specified region of Quetta. The approach involves merging various thematic layers into GIS 10.8 environment, in combination with a DEM, LULC, precipitation map, and soil map.

Table 1: Datasets types and its sources of acquisition

Dataset Type	Resolution	Data source
DEM	12.5 m	https://asf.alaska.edu/data-sets/derived-data-sets/alos-palsar-rtc/alos-palsar-radiometric-terrain-correction/
LULC	10 m	https://livingatlas.arcgis.com/landcover/
NDVI	10 m	https://dataspace.copernicus.eu/
Soil type	1 km	https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v20/en/
	250m	https://www.soilgrids.org/
Precipitation	5.3 km	CHIRPS || Google Earth Engine

RUSLE model parameters estimation

The Revised Universal Soil Loss Equation (RUSLE) is widely-adopted empirical model that serves to estimate soil erosion developed by Renard (1997).This model takes into account various important factors that influence the erosion process of soil. These factors include rainfall intensity, the capacity of soil to erode, slope length, and the extent of vegetation cover. By considering all these factors, the RUSLE provides a comprehensive analysis of the potential risk of soil loss in a given area, making it an important tool for soil conservation and land management. RUSLE is an upgraded version of the Universal Soil Loss Equation (USLE), which was developed by Wischmeier and Smith (1978). Nowadays, RUSLE is widely accepted model/equation, used to estimate the potential annual soil loss. The RUSLE model by Renard (1997) was computed using **Equation 1**:

$$A = R * K * LS * C * P \tag{1}$$

Where, A denotes soil loss over a selected period, usually on yearly basis; R represents rainfall-runoff erosivity index/factor; K represents the soil erodibility factor; LS denotes the length of slope (L) and slope gradient (S) factors; C represents the cropping management factor; while P denotes the supporting conservation practice factor. The methodological framework is presented in the following flowchart (**Figure 2**).

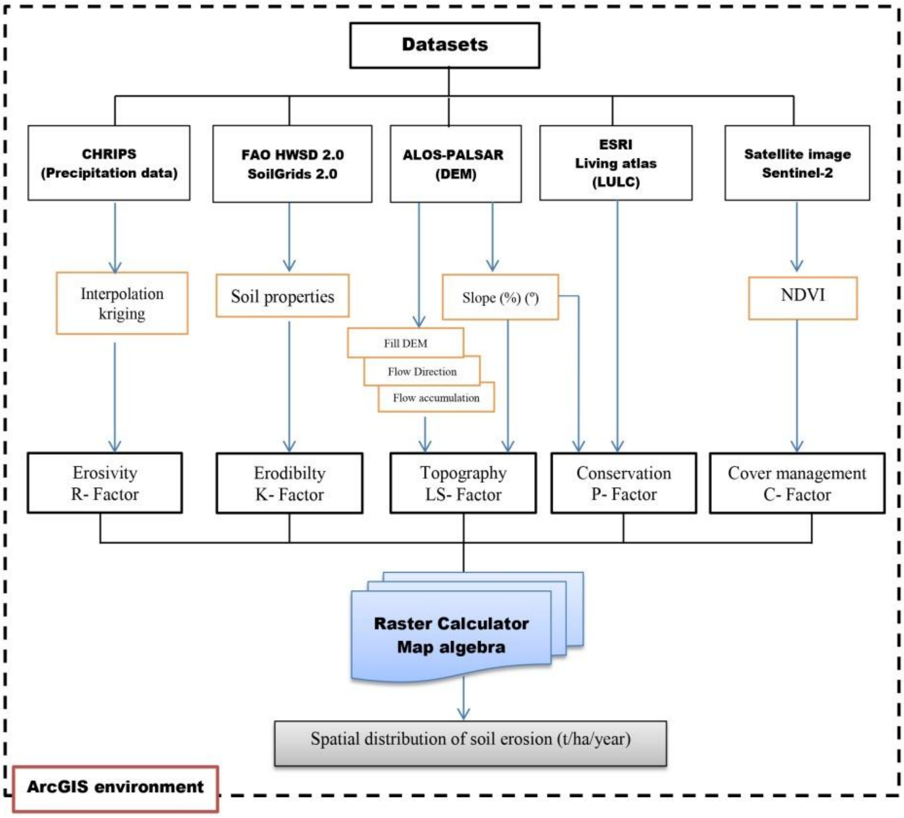

Figure 2.Methodological framework of the study

Rainfall erosivity factor (R) estimation

The R-factor is an essential parameter that replicates the impact of rainfall intensity on soil erosion, making it a vital component in accurately assessing soil erosion in a specific area (Wischmeier & Smith, 1978). It estimates the impact of rainfall in the form of kinetic energy and predicts the amount of runoff which is directly interconnected with the precipitation events in a region (Ghosal & Das Bhattacharya, 2020). The R-factor for RUSLE model input was calculated by **Equation 2** developed by Singh *et al*. (1981) as follow:

$$R = 79 + 0.363 * AAP \tag{2}$$

Where, R signifies the rainfall erosivity and AAP is Average Annual Precipitation rate.

In the light of insufficient weather station data, the CHIRPS precipitation data (from 2000-2023) was employed. The precipitation values for each grid cell were obtained in tabular format from Google Earth Engine. The Kriging interpolation in ArcGIS environment was then used to generate a continuous spatial distribution of precipitation for study area (Sadeghi *et al*., 2017).

Soil erodibility factor (K) estimation

The K-factor is a vital parameter that measures the susceptibility of soil to erosion. It is determined by analyzing the physical structure and profile characteristics of the soil (Renard, 1997). The K-factor reflects how easily soil particles detach and move due to rainfall and runoff. While the texture plays the most significant role in determining K, factors like soil structure, organic matter content, and permeability also contribute (Stone & Hilborn, 2012).

There are various equations utilized for the estimation of K-factor concerning annual soil loss. As per the suitability to our study area, **Equation 3** was used developed by Wischmeier and Smith (1978):

$$K = [(2.1 \times 10^{-4} M^{1.14}(12 - OM) + 3.25(S - 2) + 2.5(P - 3)] / 759 \quad (3)$$

Where, K represents the soil erodibility factor, M represents the grain size parameter, which is the product of the silt content (%) with (100% clay)**,** OM represents % of organic matter, S is soil structure and P denotes permeability class of the soil.

As local soil data for the region is not readily available, we have utilized the Harmonized World Soil Database (HWSD) v2.0 and SoilGrids 2.0 to provide us with the necessary information. Developed collaboratively by FAO/IIASA/ISRIC/ISS-CAS/JRC in 2009, HWSD 2.0 offers the soil information for the entire world, broken down into 221 million grid cells across a detailed attribute database.it covers 21,600 rows and 43,200 columns, which provides a granular level of information for analysis. In contrast, SoilGrids 2.0 employs cutting-edge Machine Learning methods to generate the essential models using soil observations from around 240,000 locations worldwide, along with over 400 global environmental covariates describing vegetation, terrain morphology, geology, climate and hydrology (Poggio *et al*., 2021).

Topographic factor (LS) estimation

The LS factor is a crucial indicator that determines the relationship between two key terrain features; the length of slope (L) and steepness of the slope (S). The LS measures the collective impact of these two factors on soil erosion, providing valuable insight into the topography of the land. Many of the researchers have developed their own slope steepness factor while utilizing the slope length factor from Wischmeier and Smith (1978).In current study LS factor was calculated by **Equation 4** developed by Moore and Nieber (1989) as follow;

$$LS = \ln\left(\frac{A_s}{22.13}\right)^n \left(\frac{\sin\beta}{0.0896}\right)^m \quad (4)$$

Where, A_s represents the catchment area, while β denotes the slope gradient in degrees, n = 0.4 and m = 1.3. The **Equation 4** was initially developed by Moore and Burch (1986) based on the unit stream power theory. But this equation is more suitable for calculating flow in landscapes with complex topographies than the original empirical equation. The "A_S" term in the equation.4 accounts for the both flow divergence and convergence (Moore & Nieber, 1989).

Cover and management factor (C) estimation

The C-factor is a significant measure used to assess the influence of different land management techniques, such as cropping and cover management, on the process of soil erosion. It takes into account the effects of factors such as the type of vegetation, the planting density, and the level of ground cover on the soil's ability to resist erosion rate (Koirala *et al.*, 2019). In order to determine the annual soil loss, a range of methods are utilized to calculate the C-factor. In this specific analysis, we have implemented a methodology that derives the C-factor through the assessment of vegetation indices, including the Normalized Difference Vegetation Index (NDVI), as outlined by Alexandridis *et al*. (2015).For this estimation, firstly NDVI was calculated using **Equation 5** as defined by Tucker (1979):

$$NDVI = \left(\frac{NIR - RED}{NIR + RED} \right) \quad (5)$$

The C-factor was then calculated by equation 6,as described in the study by Toumi *et al*. (2013).

$$C = 0.9167 - NDVI \times 1.1667 \quad (6)$$

Any positive value of C greater than 1 and negative value less than 0 was rescaled to the range of 0 and 1 in ArcGIS environment using “Raster Calculator”.

Conservation support practice factor (P) estimation

The P-factor is a measure of the effectiveness of a particular support practice in reducing soil loss over a region. Precisely, it is the ratio of soil loss when using a given conservation practice, compared to the amount of soil loss that would occur if the land were cultivated in the traditional up and down manners (Wischmeier & Smith, 1978). It refers to the set of techniques and methods that aim to slow down and weaken the flow of runoff, while also curtailing the extent of soil erosion (Yue-Qing *et al*., 2009). In order to evaluate the effectiveness of management activities, the P-factor is a useful metric that ranges from 0 to 1. A value of 1 indicates good practices, while values closer to 0 represent poor practices. Traditionally, slope percentages have been used to determine suitable P-factor values. However, in this research, a combined approach utilizing both LULC and slope percentage was employed to calculate the P-factor. LULC classes were assigned appropriate values based on their contribution to erosion, and slope values were also taken into consideration. The resulting P-factor values (**Table 2**) were then utilized to assess the level of erosion risk in the study area.

Table 2: Conservation practice values (Wischmeier & Smith, 1978)

Slope (%)	Land use types	P values
0 – 5	Agriculture land use	0.1
5 – 10	Agriculture land use	0.12
10 – 20	Agriculture land use	0.14
20 – 30	Agriculture land use	0.19
30 – 50	Agriculture land use	0.25
>50	Agriculture land use	0.33
0-100	Other Land use	1

RESULTS AND DISCUSSION

The RUSLE model has been utilized in numerous studies and achieved acceptable results. RUSLE method calculates the erosion rate on the bare slope for any given time period by using five factors: rainfall erosivity (R-factor), soil erodibility (K- factor), topography (LS-factor), cover management (C- factor), and support practice (P-factor). The attained results are summarized as follow.

Rainfall erosivity factor (R)

The study area of Quetta sub-basin lies in semi-arid climatic zone of the province. The province experiences the influence of two distinct meteorological phenomena, namely Western disturbances and Monsoon. In rare cases, oceanic and monsoon currents arising from the Arabian Sea can also extend to the southern region of the watershed, resulting in considerable precipitation. In the northern areas, the primary source of rainfall is Western disturbances, which are more common during the months of February and March. Conversely, Monsoon is the pivotal source of rainfall in the southern regions of the Province, with major storms occurring in July and August. The average annual rainfall value of 188 to 309 mm indicated a moderate amount of rainfall. More than 60% of the area (Northern mountainous zones) was found to be experiencing more than 236mm rainfall annually. Overall, the precipitation distribution was experiencing an increasing gradient from North to South (**Figure 3**).

The total amount of precipitation that occurs in a specific area is directly associated with the erosivity rate. The R-values of the study area (**Figure 4**) varied between 147 and 191 MJ mm/ha/hr/year, suggesting a moderate to high risk of erosion, especially on sloping lands of the northern and north-eastern part of the study area. In **Table 3**, various classes of the R factor are portrayed together with their corresponding areas. Notably, 54% of the area exhibits high to very high values of the rainfall erosivity factor. Approximately 23% of area indicates a moderate level, while 23% demonstrates a low to very low R factor value for the study area. It is evident that there is a strong correlation between the distribution of rainfall and the erosivity factor. As rainfall decreases, the erosive force in the area also diminishes.

Table 3: Distribution of R-factor classes in Quetta sub-basin

S.No	R-factor classes	Area(km²)	Area (%)
1	147.370 - 155.472	191.3761	10.97
2	155.472 - 164.608	220.964	12.67
3	164.608 - 172.193	393.8949	22.59
4	172.193 - 181.156	665.5856	38.17
5	181.156 - 191.327	271.8022	15.58

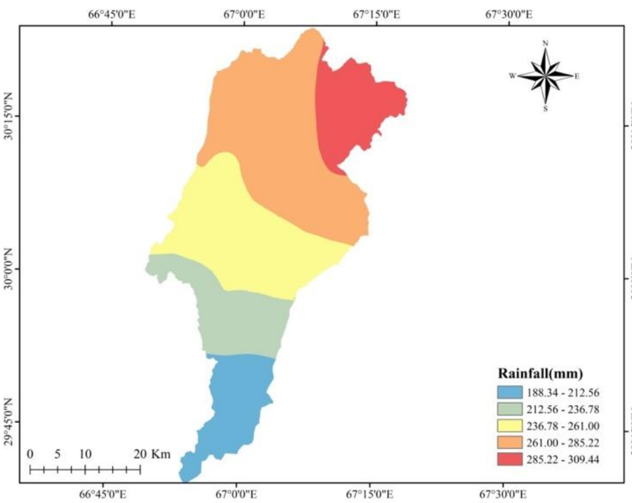

Figure 3: The rainfall map of Quetta sub-basin

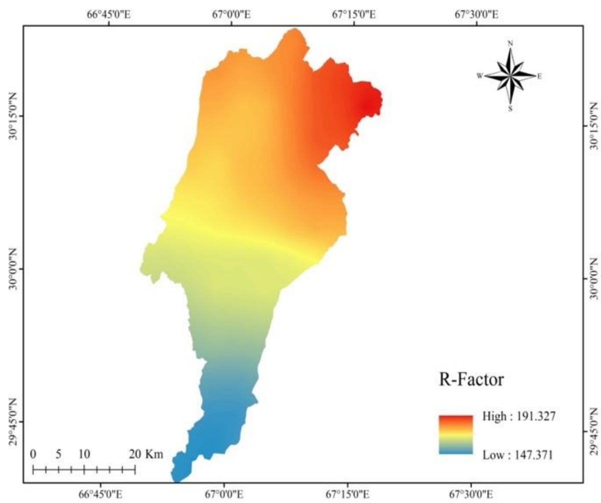

Figure 4: The R-factor map of Quetta sub-basin

Soil erodibility factor (K)

The Quetta sub-basin comprises of seven distinct types of soil namely; Calcisols, Cambisols, Fluvisols, Gypsisols, Leptosols, Luvisols, and Regosols (**Figure 5**). The Calcisols are the most prevalent soil type, covering 1347.64 km² of the study area. Regosols cover nearly 300 km², while leptosols cover 88.36 km², Cambisols cover 5.5 km², fluvisols cover 3 km², gypsisols cover 0.65 km², and luvisols cover an area of 0.1 km². (https://soilgrids.org). The K factor reflects the natural erodibility of the soil, influenced by the properties like texture, organic matter contents, and its internal structure. The erodibility value of a soil is an important parameter that indicates its vulnerability to erosion. A soil with an erodibility value closer to 0 is less prone to erosion, whereas a value closer to 1 suggests that the soil is highly susceptible to erosion. In the study area, the most common soil texture is loam, and the K-factor values range from 0.0229 to 0.0259, (**Figure 6** and **Table 4**). Among the different types of soil present in study area, Gypsisol and Fluvisol have the highest K-factor values at 0.0259 and 0.0258, respectively. On the other hand, the Luvisols and Cambisols exhibit the lowest erodibility values in this study, indicating a higher level of resistance to the erosion process.

Table 4: Distribution of K-factor classes in Quetta sub-basin

S.No	K-factor classes	Area(ha)	Area (%)
1	0.0229 - 0.0235	9395.05	5.3930
2	0.0235 - 0.0241	134707	77.325
3	0.0241 - 0.0249	29790.74	17.100
4	0.0249 - 0.0259	315.16	0.1809

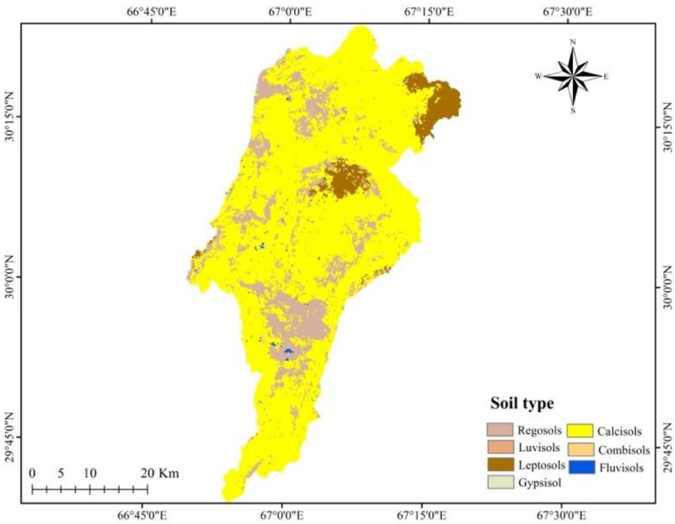

Figure 5: The soil types map of Quetta sub-basin

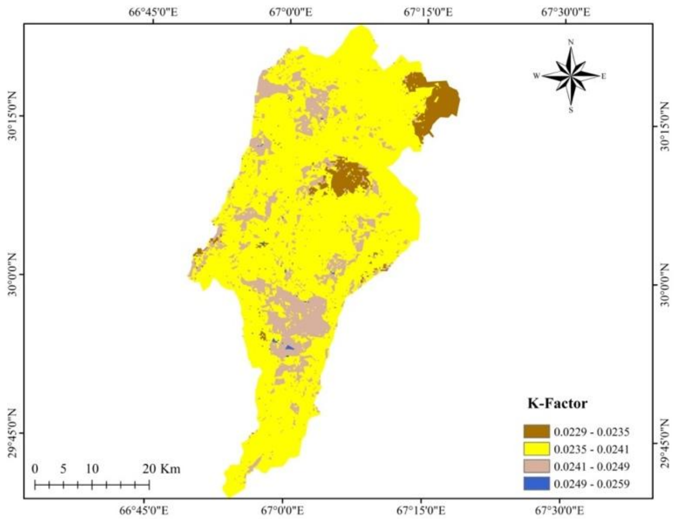

Figure 6: K-Factor map of Quetta sub-basin

Topographic factor (LS)

The study area features a diverse topography, ranging in elevation from 1548 to 3532 meters. It is defined by high-elevation mountainous regions in the North (Takatu range) and North-eastern (Zarghoon range) areas, as well as along the sub-basin's boundary (**Figure 7**). The LS values ranges from 0.0022 to 360.77 (**Table 5**). Areas with values below 5.66 are mostly comprised of lowland terrain, encompassing the majority of the study area. Meanwhile, values exceeding 16.98 indicate rugged terrain with steep slopes surrounding the lowlands (**Figure 8**).

Table 5: Distribution of LS-factor classes in Quetta sub-basin

S. No.	LS-factor classes	Area(ha)	Area (%)
1	0.00224 - 5.661	101526	58.227
2	5.661 - 16.979	37837.43	21.700
3	16.979 - 32.542	25040.91	14.361
4	32.542 - 59.422	8621.92	4.945
5	59.422 - 360.770	1336.6	0.767

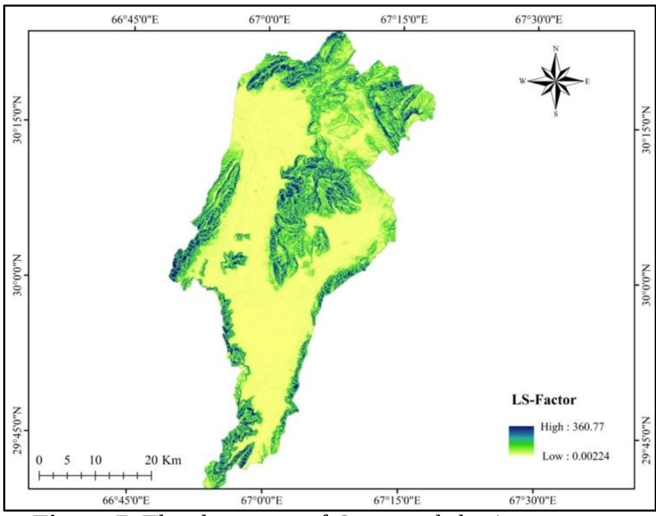

Figure 7: The slope map of Quetta sub-basin

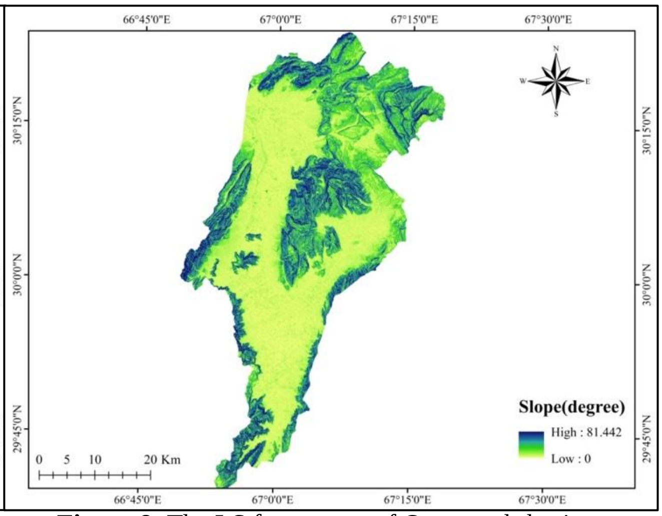

Figure 8: The LS factor map of Quetta sub-basin

Cover and management factor (C)

The C-Factor for the year 2023 was determined through NDVI calculations, wherein a range of values between -0.25 and 0.56 were obtained (**Figure 9**). These values served as an indicator of vegetation health, with higher values indicating healthier vegetation and lower values indicating the absence of vegetation, such as barren land and water bodies. Finally positive value of C greater than 1 and negative value less than 0 was rescaled to the range of 0 and 1 in ArcGIS using "Raster Calculator". The C-Factor values range from 0.001 to 1(**Figure 10**). Predominantly, it was observed that over 80% of the total area have a higher C-Factor value, enlightening low vegetation and barren land.6% of study area has low C-factor indicating vegetation cover (**Table 6**).

Table 6: Distribution of C-factor classes in Quetta sub-basin

S. No.	C-factor classes	Area(ha)	Area (%)
1	0.001 - 0.388	2770.86	1.589124
2	0.388 - 0.529	8383.49	4.808039
3	0.529 - 0.588	77288.19	44.32576
4	0.588 - 0.745	85811.9	49.21422
5	0.745 - 1	109.59	0.062851

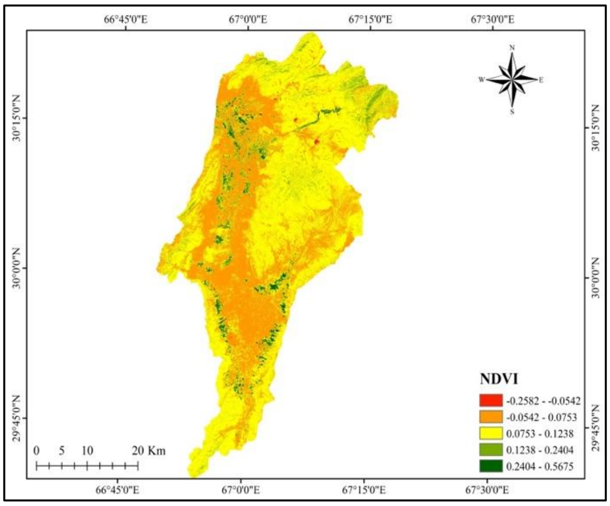

Figure 9: The NDVI map of Quetta sub-basin

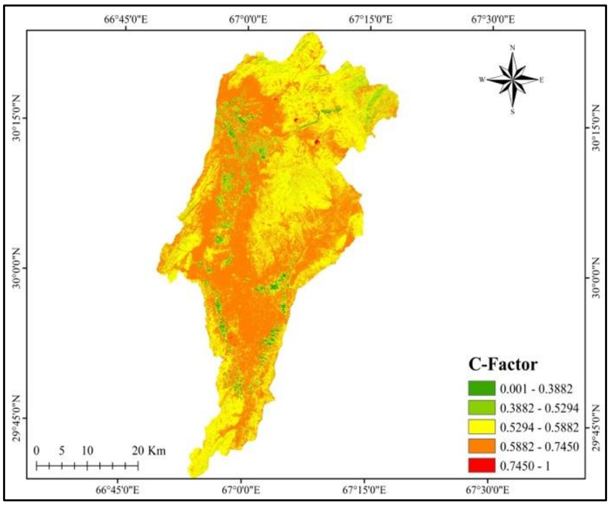

Figure 10: The C-factor map of Quetta sub-basin

Conservation support practice factor (P)

The P-factor is a metric that quantifies the adherence to good or poor practice in land management, which can range from 0 to 1. A score of 1 indicates that the land is being managed with good practices, while scores closer to 0 indicate a lack of good practices. The P-factor is determined by considering the combined effects of slope (%) and land use/cover (LULC), using predefined values. The resulting P-factor values range from 0.1 to 1, with 0.1 indicating poor practice and 1 indicating good practice. The built-up areas, rivers, and agricultural lands consistently receive a score of 1 for good practice, as demonstrated in research conducted by Morgan *et al*. (1999) and Wischmeier and Smith (1978).

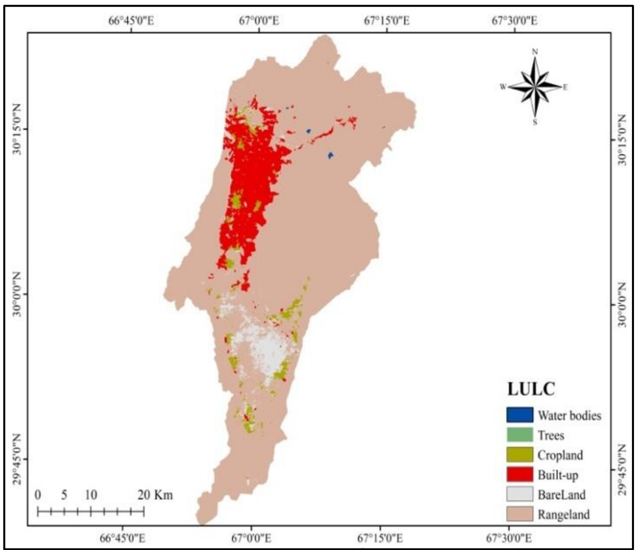

Figure 11: The LULC map of Quetta sub-basin

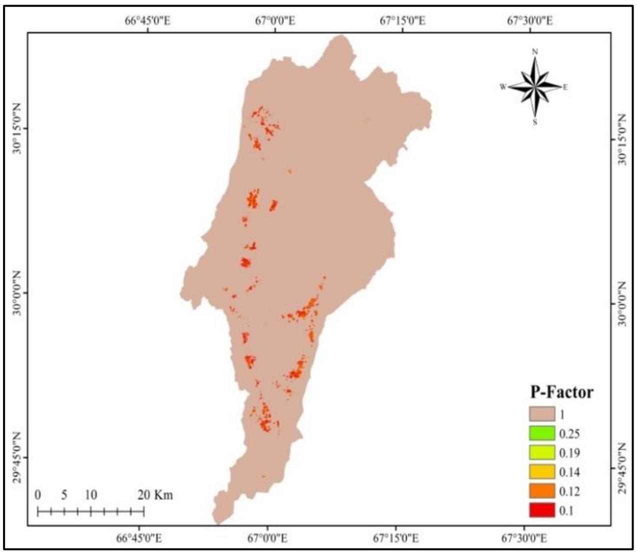

Figure 12: The P factor map of Quetta sub-bason

Estimation of annual soil erosion (A)

Finally, the soil erosion equation was employed by multiplying all the factors (R, K, LS, C, and P) to represent the annual soil erosion (A) in the Quetta sub-basin, Pakistan. Before the overlay analysis, all the thematic layers were projected with WGS84/UTM Zone 42 N datum coordinate system in a resampled resolution of 10*10m for uniform usage in the ArcGIS environment. The resultant map was reclassified using natural break (Jenks), into five classes: very low, low, moderate, high and very high erosion severity class. The results are showcased in **Figure 13**, which vibrantly portrays the distribution of soil loss in the study region. The statistical observations in **Table 7** revealed that the levels of soil erosion vary significantly, ranging from 0 to 866.34 (tons/ha/year). The majority of the study area, approximately 58%, is categorized under the very low erosion severity class, with an erosion rate less than 13.58 t/ha/year. Low soil erosion, in the range of 13.58-44.16 t/ha/year, is found in 24% of the study region. However, the northern part (Takatu range),north-eastern part (Zarghoon range) eastern-central (Murdar range), and west-southern part (Chiltan range) of the study area, which are characterized by steeper slopes and barren land, experience high to very high levels of soil erosion, ranging from 81.53-866.34 t/ha/year. Moderate erosion, in the range of 44.16 – 81.53 t/ha/year, covers 13% of the study area and takes place in the foothills of the mountains where agricultural land with trivial slopes exists. Overall, the current model identifies areas at risk, where management actions are required.

Table 7: Spatial distribution of soil erosion in Quetta sub-basin

No.	Soil erosion rate (tons/ha/year)	Area (hectare)	Covered (%)	Erosion Severity Class
1	0.000 - 13.589	100799.3	58.060	Very Low
2	13.589 - 44.166	41793.14	24.072	Low
3	44.166 - 81.538	22368.01	12.883	Moderate
4	81.538 - 146.089	7472.98	4.304	High
5	146.089 - 866.346	1178.21	0.678	Very High

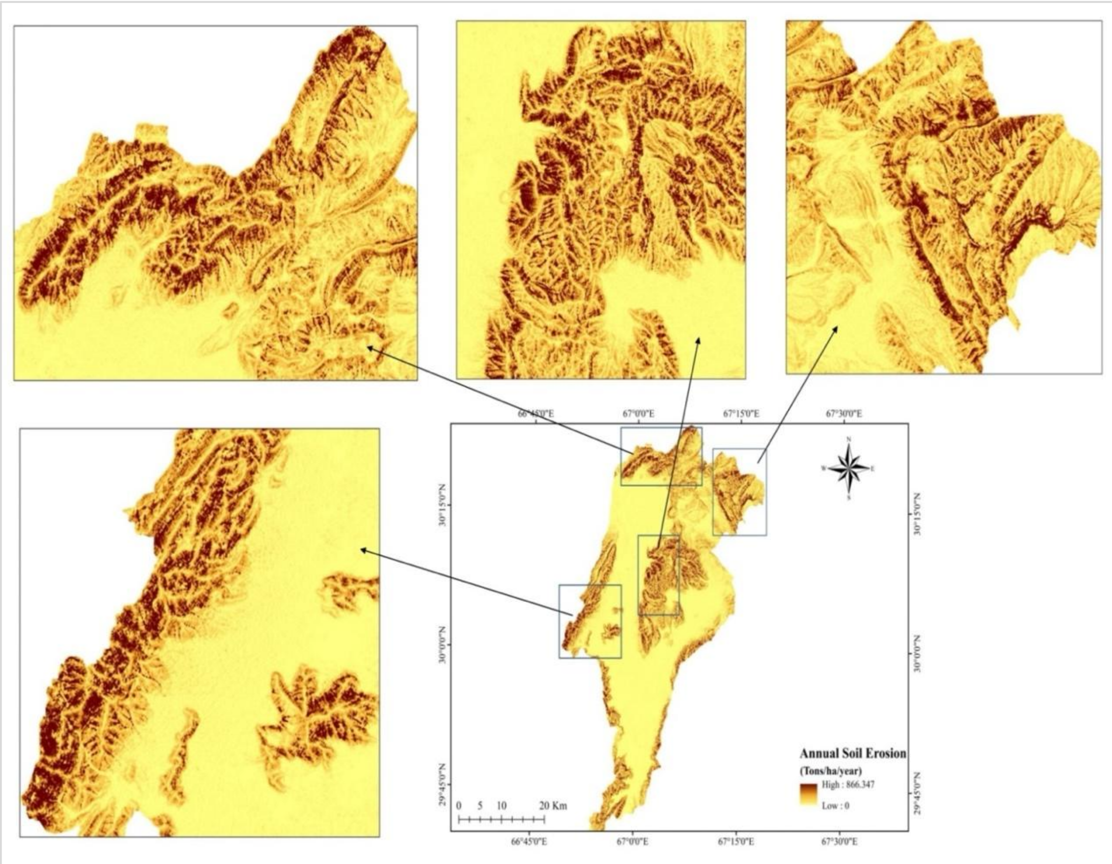

Figure 13: Annual soil erosion in Quetta sub-basin

CONCLUSION

In this study, the RUSLE model was employed with geospatial data and GIS tools to estimate the annual soil erosion in Quetta, Pakistan. A total of five factors were examined in this study including rainfall erosivity (R-factor), soil erodibility (K-factor), topography (LS-factor), cover management (C-factor), and support practice (P-factor).The Annual Soil Erosion model has revealed that the study area is characterized by varying degrees of soil erosion, with erosion rate ranging from 0 to 866.34 tons per hectare per year. Areas having steep slope are more prone to very high degree of soil erosion. Conclusively Remote Sensing and GIS, in combination with the RUSLE model, are significant for identifying input factors for modeling soil erosion and natural resource management. The research findings provide significant insights into the soil erosion levels at the Quetta sub-basin, highlighting the areas that require immediate attention and remedial measures. There is no geospatial technology-based soil erosion studies conducted in the region, so this study will serve as firsthand guidance for decision-makers and planners in mitigating soil loss risk and promoting sustainable land management in the region.

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