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Research Article

Soil Erosion Assessment for the Eastern Part of Daquq District (Chai River Sides) Using a Rusle Model-Based GIS

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Abstract:

Soil erosion therefore poses as one of the severest environmental problems as it takes away with it the toiled and enriched layer of soil hence threatening crop and food production, and land productivity. The conditions such as high intensity rainfall or high relief however may make soil erosion more accentuated and therefore one would require adopting techniques and/or tools for Use advanced geospatial technologies to assess and Accurately map soil and water erosion risks in the Dakuk Chai basin. Integrating environmental factors: Incorporates dynamic environmental variables, involving land use patterns, climate change and terrain atterbuites, to deliver a wide-ranging understanding of soil erosion. In this research, the RUSLE model was utilized to assess the rate of soil erosion on the sides of what is known as the Chai River in Daquq town, Kirkuk, Iraq. In 2015, the highest soil erosion class over the study area was 0.010847 km^2, while the low soil erosion class had large areas of 29.31882 km^2. In addtion, in 2024, the very high soil erosion class covered approximately 0.01454 km^2, and the low soil erosion class occupied 29.4398 km^2 of the study area. Through this research, a deeper understanding of the phenomenon of soil erosion in Daquq was provided, which contributes to directing efforts towards protecting the environment and promoting sustainable development in Kirkuk. Overall, the results specified a significant concern regarding soil erosion within the complex area, warranting prompt attention from relevant authorities.

1. Introduction

The Dakuk Chai Basin in Kirkuk city, Iraq, faces increasing soil erosion risks due to urbanization, inadequate land management, and natural factors. However, localized studies assessing erosion susceptibility are lacking. This research aims to fill this gap by utilizing advanced geospatial techniques and remote sensing data to map erosion risks. By analysing topography, hydrology, soil characteristics, and land use patterns, this study seeks to identify erosion hotspots and assess their implications for agriculture and the environment. Ultimately, this research aims to provide crucial data for informed decision-making and the development of effective erosion control strategies in the Dakuk Chai Basin.

The loss of soil from the land surface by erosion is widespread globally and adversely affects the productivity of all natural ecosystems as well as agricultural, forest, and rangeland ecosystems [1-40]. Understanding the spatial distribution and long-term dynamic principles of soil erosion is the basis for effective regional land use management and soil erosion prevention [33]. Many methods have been developed for soil erosion assessment over the years, but quantifying soil erosion under natural field conditions, especially at the landscape scale, remains a challenge [22]. Remote sensing coupled with geographic information systems (GISs) provides key information on erosional dynamics and intensity over time and space, which is critical for providing a baseline for soil erosion assessment, control, and prediction [41-43].

Space technology, particularly satellite remote sensing, currently offers an important contribution to the synoptic and timely evaluation of natural resources over large areas [44-50]. Despite the limitations of cost and time consumption of other soil erosion models, remote sensing techniques can map erosion with less expert data, time and cost and provide the suitable quantitative information necessary for assessing and monitoring the levels of soil erosion [43]. Remote sensing may help in segmenting the landscape into internally more or less homogeneous soil–landscape units for which soil composition can be assessed by sampling using classical or more advanced methods [31]. In addition, Sentinel-2 images allowed free download and have global spatial coverage and a temporal resolution of 5 days. Moreover, new cloud-based processing technologies allow these images to be utilized on a large areas professionally. More research is required to examination Sentinel-2 images utilizing methodologies to assess abandoned land proposed by other reserchers [51-53].

Empirical models such as the universal soil loss equation (USLE), the modified universal soil loss equation (MUSLE), and the revised universal soil loss equation (RUSLE) are the most commonly used methods to predict soil erosion, especially in watershed areas, due to their minimal data requirements and ease of application [15]. Interest in the use of GIS and remotely sensed data to derive RUSLE parameters is growing [39]. Although the RUSLE is the most widely used model for the estimation of soil erosion, the factors, namely, rainfall erosivity, soil erodibility, slope length and steepness, cover management and conservation practices, vary greatly among different climatic zones, soil properties, slopes, land cover types and crop phases [21]. Therefore, the spatial distribution of erosion site and intensity can be derived by merging RUSLE and GIS. With this method, it is possible to estimate prospective soil loss and its spatial distribution at acceptable prices, with improved accuracy for bigger regions [24].

the purpose of this study is to assess soil erosion for the eastern part of Daquq District particularly in the River Chai area by applying RUSLE model and GIS techniques. In this case, it intends to study the spatial distribution, measure the likely erode rates, assess the risk levels, test the results from the models used, deduce the effects of erosion and recommend ways of addressing the problem. In addition, the RUSLE model offers a straightforward approach to assess soil erosion. By utilizing remote sensing data and GIS, RUSLE effectively assesses erosion. This reserch have established various equations to model the five factors of the RUSLE model, considering the diverse variations in the soil erosion process. The model also involve the analysis of satellite imagery with a plotted view of soil erosion.

2. Materials and Methods

2.1 Study Area

Daquq District is located southeast of Kirkuk Governorate, 300 kilometers north of the capital, Baghdad. Daquq District is bordered by Kirkuk, Chamchamal, Dur, Tikrit, and Tuz Khurmatu. The Chai Dakuk River is one of the main branches of the Al-Adhaim River. The basin extends over an area of about 3481 square kilometers and is bounded between latitudes 34°44'30"- 35°35'49" N and longitudes 44°17'39"- 45°28'16" E [7]. It flows through the center of Kirkuk and extends southward until it meets the main course of the Tigris River in eastern Iraq. It is one of the seasonal rivers, drying up in the summer. The Daquq area is distinguished by its picturesque landscapes and the fertility of its soil, making it an excellent agricultural region. One of the factors that contributed to the fertility of the soil and supported agricultural activity was the passage of the special Chai River through it. The climate of Daquq is similar to the climate of Iraq in general, being hot, dry in the summer, and mild in the winter. Figure 1 shows the study area (Chi River).

2.2 Data Collection and Preprocessing

The data collection process for our research on soil erosion encompassed a comprehensive approach, drawing from diverse sources to ensure accuracy and reliability. The Sentinel-2 mission satellite imagery was acquired in December 2015 and January 2024 and served as a cornerstone of our data acquisition strategy. These images, accessed from the Copernicus website, were meticulously selected at the L2A correction level to mitigate potential distortions arising from atmospheric conditions such as cloud cover. Through resampling, reprojection, and subsetting facilitated by the Snap program, we synthesized a land use and land cover (LULC) map, which is crucial for estimating the P (erosivity) and C (land cover) factors in the Rusle Model.

Additionally, the choice of Sentinel-2 imagery was strategic, considering its high spatial resolution of up to 10 meters, facilitating detailed analysis of land surface features.

Augmenting our dataset, a digital elevation model with a spatial resolution of 12.5 meters was procured from the USGS website, enriching our capacity to estimate land cover and topographic factors pertinent to erosion susceptibility. Figure 2 shows the digital elevation model of the study region, with elevations ranging between 229 and 388 m above mean sea level.

Rainfall data spanning December 2015 to February 2024 were sourced from the NASA Power Data Access Viewer, which focuses on 62 specific points proximal to our study area. This information facilitated the development of a rainfall (R) estimation map, which is crucial for assessing the erosive impact of precipitation patterns over time. The timing of image retrieval was deliberate, aligning with peak rainfall months (December and January) to capture environmental dynamics when precipitation-induced soil erosion is most pronounced. The annual rainfall data were downloaded from https://power.larc.nasa.gov/data-access-viewer/, which contains meteorology- and solar-related parameters formulated for assessing and dessining renewable energy systems. Annual rainfall data have been adopted since 1995 for 53 points in the study area and its surrounding areas.

Furthermore, a soil map obtained from the FAO website provided insights into the soil composition within the study area, complementing our understanding of soil erosion processes and informing land management strategies.

Using satellite imagery data, elevation models, records of rainfall, and soil maps, the present study aims at examining the multidimensional antecedents of soil erosion to assist authorities, policymakers, and environmentalists enhance environmentally sustainable practices and strategies for land use. Table 1 shows the information on technical specs and data sources.

2.3 RUSLE Model

The simplest method used in estimating soil loss rates is the empirical model, the RUSLE model (Revised Universal Soil Loss Equation) [8]. It has been utilized for more than forty years, and it bases on the USLE concept [26]. RUSLE is an empirical model used in soil erosion estimation whose procedures are globally recognized and applied. Several studies have shown this; for instance, [21] in their puplication. Commonly, the RUSLE method is applied with the purpose of determining the risk and the loss resulting from the erosion of the territory of interest. It provides procedures for designing conservation measures and combating soil erosion by water across the different land-use cover types such as croplands, rangelands, and disturbed forest lands [46]. Although the model of RUSLE has been formerly used for predicting the amount of soil erosion in many regions of the world, the factors of rainfall erosivity, soil erodibility, slope length, slope, cover, and management and conservation practice are known to differ remarkably depending on the climate region, soil type, slope gradient, and land cover as well as the different crop phases [21].

The original USLE rainfall runoff factor was superseded by the rainfall erosivity factor in RUSLE. The soil erodibility factor (K), slope length and steepness factor (LS), land cover management factor (C), and support practice factor (P) continue identical [5].The fundamental premise of the RUSLE is that the sediment content of the flow regulates detachment and deposition. Erosion is not restricted by the source; rather, it is constrained by the flow carrying capacity [20].

However, the estimation of certain input parameters of the RUSLE may necessitate extensive field and laboratory investigations. Consequently, these parameters are typically estimated using alternative methods [45]. RUSLE continues to be utilized extensively, as the majority of users find certain models, such as the WEPP, to be challenging to operate [23].

In a variety of contexts, including mountainous tropical watersheds, large-scale watersheds, agricultural dominant watersheds, areas with distinct wet and dry seasons, and areas with dynamic changes such as land cover patterns, agricultural farmlands, and development, the application of the RUSLE in a GIS framework has been implemented [23]. Nevertheless, the RUSLE model is one of the few erosion models that, to the best of our understanding, has the potential to be applied on a global scale. This is primarily due to its straightforward structure and empirical foundation [32].

Furthermore, the model is highly effective in ungauged catchments, its data requirements are relatively low, and most importantly, it seamlessly integrates with GIS, thereby facilitating the scaling of the soil erosion process [26].

In our study, we used the RUSLE Model to estimate soil erosion in addition to the Chy River in Daquq District, Kirkuk, Iraq. The model was applied for two years, 2015 and 2024, to detect changes in soil loss. Equation (1) shows the evaluation of soil loss.

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

where:

A = Estimated average annual soil loss (tons per acre per year) (t $ha^{-1}\ y^{-1}$)
R = Rainfall-runoff erosivity factor
K = Soil erodibility factor
LS = Slope length and steepness factor
C = Cover and management factor
P = Support practice factor
Figure 3 illustrates the framework for estimating soil erosion in the study area based on the RUSEL model. Six parameters were used in the RUSLE model and were determined via the GIS technique.

2.4 Rainfall-Runoff Erosivity

The probable factors of influence to soil erosion include the amount of precipitation and the speed of rains at a certain region, which affects the strength of force exerted by raindrops on the soil, thus eroding it. The R factor specifies rain action and measures the potential of rainfall in eroding the surface [21]. The rainfall-runoff erosivity factor (R) of RUSLE is one of the prime parameters defining the degree of water erosion intensity [12]. In the RUSLE model, rainfall erosivity is the energetic capacity of rains to produce soil detachment and transport by sheet and rill erosion and therefore is not an anthropogenic factor related to land-cover management [19]. Rainfall erosivity is defined as the quantity of energy that accompanies: The impact of raindrops and the rate at which runoff water moves. The R-factor describes SHEED and RILL erosion because it is needed to quantify kinetic energy and intensity of rainfall in terms of, a long-term average.

Table 1. *The specifications and sources of the data used in this study*

Data	Source	Discription
Digital Elevation Model	https://earthexplorer.usgs.gov/ USGS	Spatial resolution 12.5 m * 12.5 m
Satellite images (Sentinel L2A)	https://dataspace.copernicus.eu/	Spatial resolution = 10 m, 20 m, 60 m GRANULE/L2A_T38SMD_A035868 Aquisision Date = Janauary 18, 2024 & Spatial resolution = 10 m, 20 m, 60 m GRANULE/L2A_T38SMD_A002663 Aquisision Date = December 26, 2015
Rainfall	https://power.larc.nasa.gov/data-access-viewer/ NASA	Output File Format :CVS
Soil Map	https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/faounesco-soil-map-of-the-world/en/	Spatial distribution map of soil types

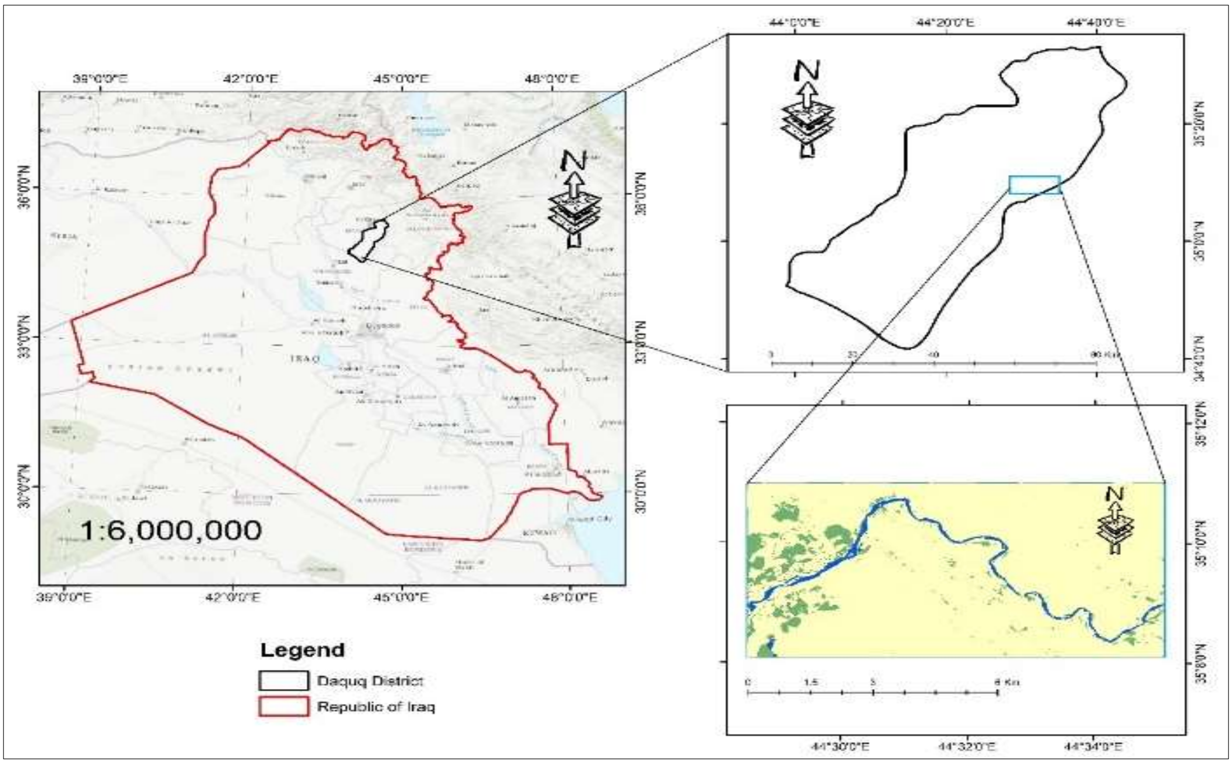

Figure 1. *Study area of this research (Chi River, Daquq, Kirkuk, Iraq)*

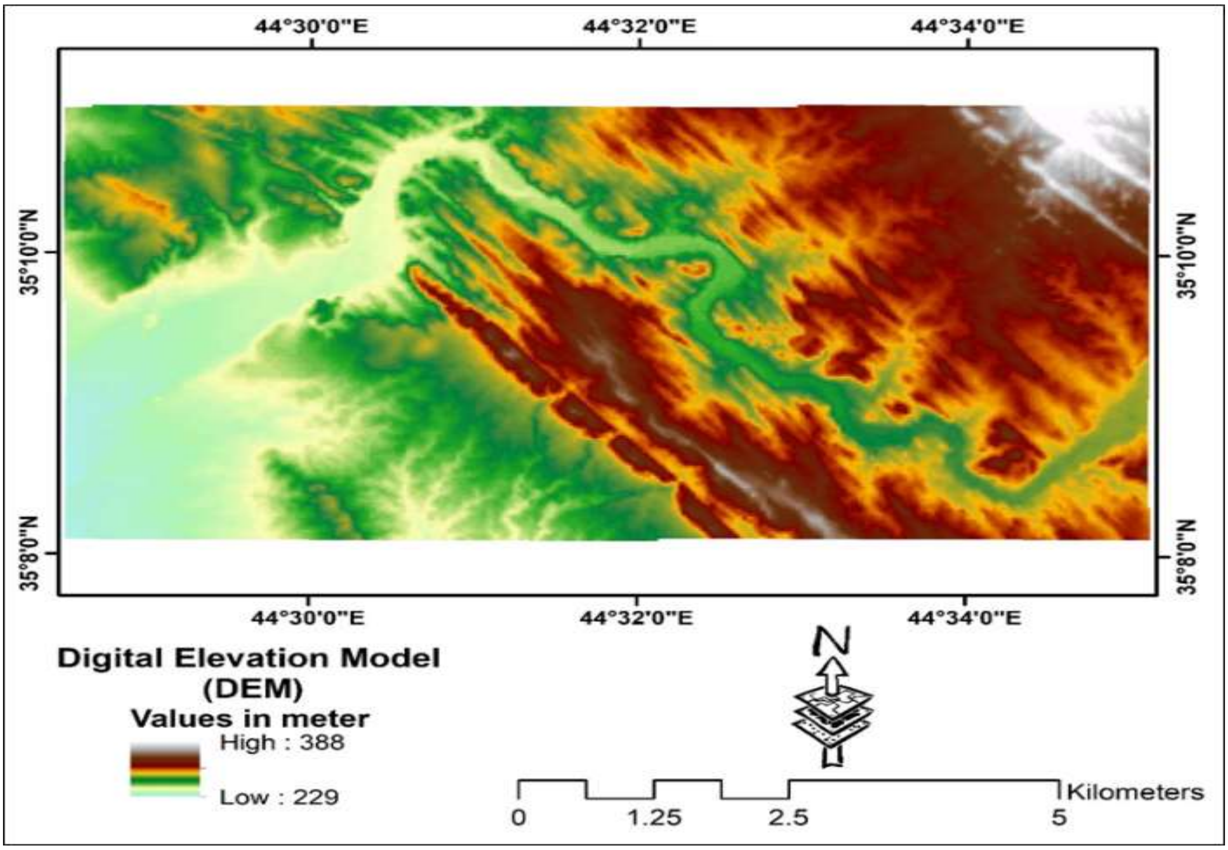

***Figure 2**. Digital elevation model of the study area*

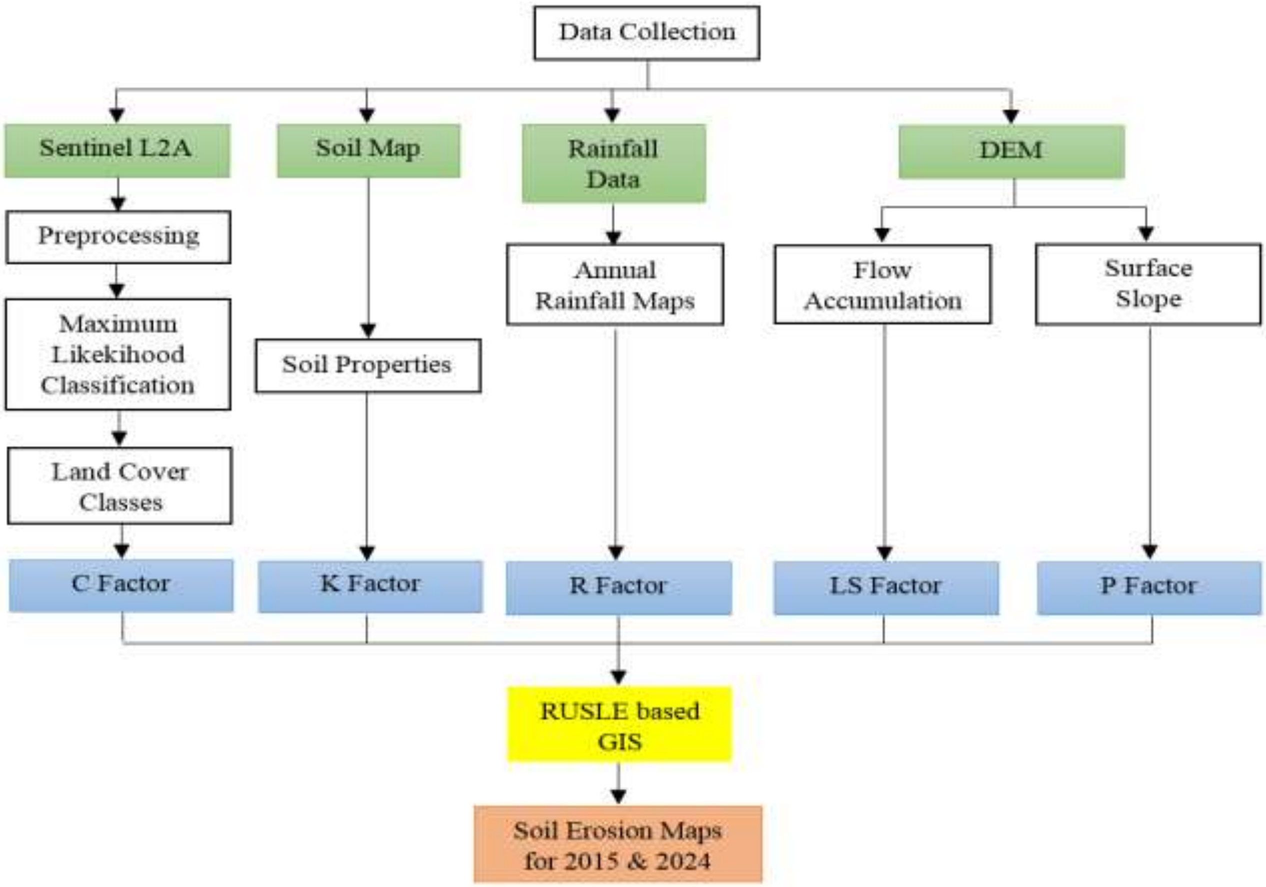

***Figure 3.** Flowchart of overall methodologies*

The value of rainfall erosivity is calculated by the product between the kinetic energy and the maximum intensity of rainfall cumulatively measure in a 30-min interval in course of a single pour [37]. This is true for the simple rainfall erosion index denoted by EI30 which measures the intensity of rainfall and its direct runoff [17].

Alterations in the intensity of rainfall serve as a prominent sign of climate change. It significantly influences agriculture as a primary factor contributing to soil erosion [47]. Accurate assessment of rainfall erosivity necessitates the use of either continuously recorded rain gauge data or high-frequency time interval precipitation recordings, preferably at subhourly intervals. However, obtaining such data is challenging in numerous regions globally, and even if accessible, the availability of such data is restricted to a shorter duration [47].

2.5 Inverse Distance Weighted

Inverse distance weighting (IDW) is one of the most frequently employed interpolation methods [2]. The interpolation of rainfall data using IDW may provide more precise results during the dry season than during the flood season [1]. The spatial rainfall field can be derived by interpolating data across a complete catchment using IDW [13]. The rainfall data were mapped spatially using the IDW interpolation technique. Figure 4 shows the RREFs for 2015 and 2024 in the study area. The R value is estimated using equation (2):

$$R = 23.61 \times \exp\ (0.0048 \times Map) \qquad (2)$$

where:

The spatial distribution map of rainfall over the study region

2.6 Soil erodibility factor

Soil erodibility, represented by the K-factor in commonly utilized soil erosion models such as the USLE and RUSLE, is a crucial component of soil erosion modelling [36]. Consequently, the evaluation of erosional soil losses serves as the foundation for effective conservation planning and management of vulnerable ecosystems [28]. The K factor is determined by the rate of soil loss per rainfall erosion index unit computed on a unit plot [13]. This property is considered by many to be a constant value that is intrinsic to the soil. This factor is indicative of the fact that soils vary in their rate of erosion when the other factors that influence erosion are identical [49].

Physical, chemical, biological, and mineralogical properties all influence the soil erodibility factor [49]. Highly permeable soils, such as sandy soils, have a greater capacity for infiltration and are more susceptible to water erosion [41]. This is because these soils readily allow water to infiltrate and are quickly swept away. However, stable aggregates have the ability to withstand the impact of rain, thereby preventing soil erosion even in the presence of runoff [28]. The stability of soil aggregates is crucial to preserving favorable physical conditions in the soil and ensuring sustainable crop productivity. The presence of iron and aluminum oxides, along with organic materials, enhances the stability of soil aggregates [18]. Figure 5 shows the soil erodibility factor (K) of the study area. The following equations (3 to 8) clarify the calculation of the K factor.

$$K_{usle} = f_{csand} \times f_{cl-si} \times f_{orgc} \times f_{hisand} \qquad (3)$$

$$k_{rusle} = K_{usle} \times 0.1317 \qquad (4)$$

where k_{usle}: Soil erodibility factor of the USLE model

$$f_{csand} = \left[0.2 + 0.3\, exp\left(-0.256 \times m_s \times \left(1 - \frac{m_{silt}}{100}\right)\right)\right] \qquad (5)$$

$$f_{cl-si} = \left(\frac{m_{silt}}{m_c + m_{silt}}\right)^{0.3} \qquad (6)$$

$$f_{orgc} = \left(1 - \frac{0.25 \times orgC}{orgC + exp\,[3.75 - 2.95 \times orgC]}\right) \qquad (7)$$

$$f_{hisand} = \left(1 - \frac{0.7 \times \left(1 - \frac{m_s}{100}\right)}{\left(1 - \frac{m_s}{100}\right) + exp\left[-5.51 + 22.1 \times \left(1 - \frac{m_s}{100}\right)\right]}\right) \qquad (8)$$

ms: the percentage of sand fraction content (0.5-2 mm particle diameter) [%]

milt: the percentage of silt fraction (0.002-0.05 mm particle diameter) [%];

mc: the percentage of clay fraction (<0.002 mm particle diameter) [%];

orgC: the percentage of organic carbon fraction content) [%].

2.6 Slope Length Factor

The LS-factor, which is the combined slope length and slope angle, exerts the most significant impact on soil loss across Europe among the six input layers. The S-factor quantifies the influence of slope gradient, while the L-factor characterizes the significance of slope length [37]. The LS-factor was initially developed for slopes with an inclination of less than 50% and has not undergone testing on steeper slopes [42].

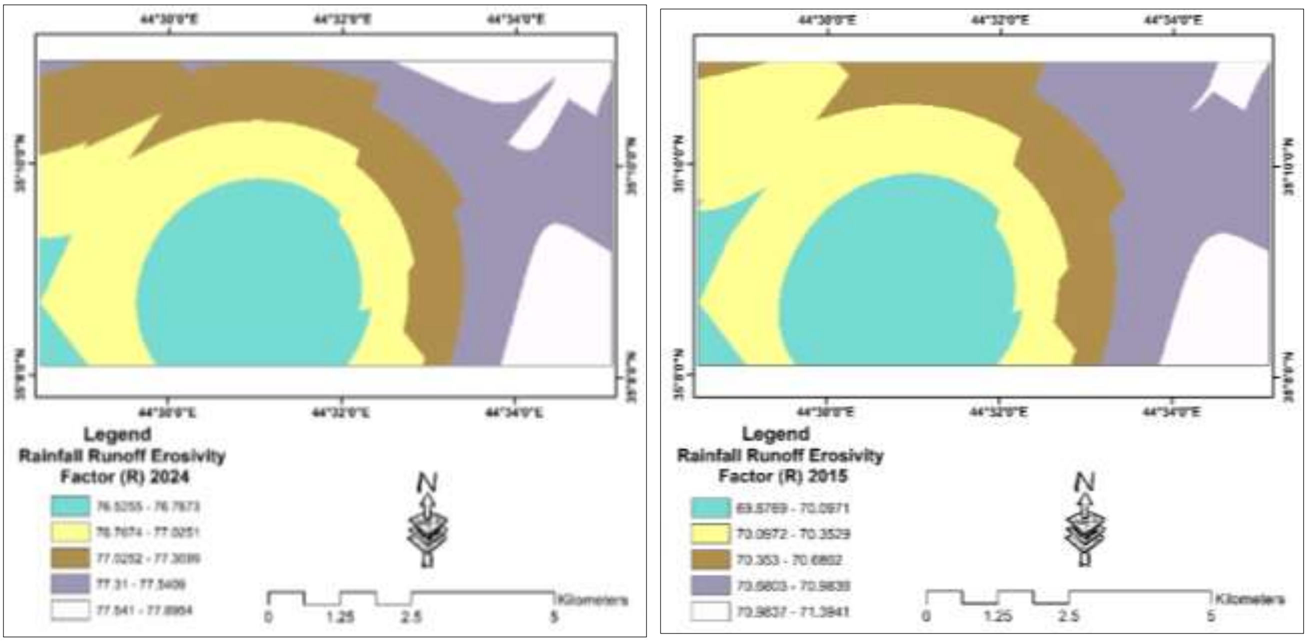

Figure 4. *Rainfall runoff erosivity factor for 2015 and 2024 in the study area*

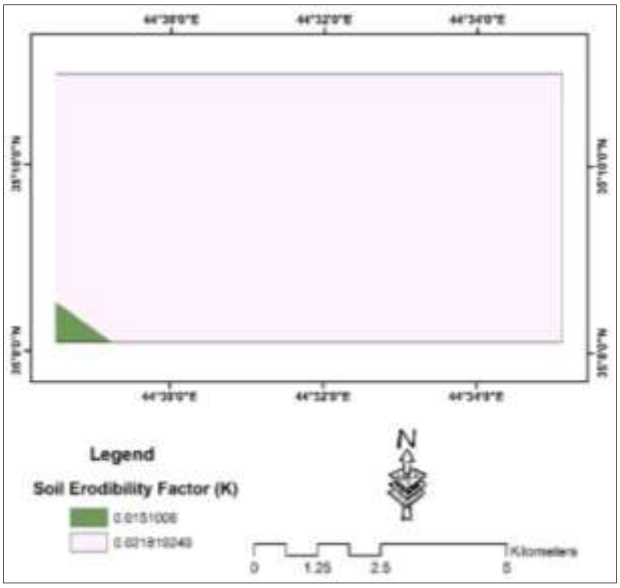

Figure 5. *Soil erodibility factor (K) of the study area*

It is defined as a unitless quantity and the values of LS- factor are always 0 or higher greater [37]. This is influenced by the LS factor of the land, which is the composite of both the slope length (L) sub factorsubfactorand the slope steepness (S) sub factorssubfactors; the overall effect that the topographic features of the land has on the erosion of hillslopes. Specifically, the LS factor regarded for delivering highly detailed data and has a significant influence in the calculation of the RUSLE equation [52]. The total amount of runoff is also exacerbated by the increase in the length of the slope formed as a result of the lengthened slope length. Likewise, when the slope of the land rises to gradient, the velocities of the runoff that leads to erosion are higher [14]. The calculation of the factor L is more complicated than the factor S. However, the factor L is essential for performing the RUSLE erosion model [10]. In modern times, this factor is frequently calculated using GIS software and a digital elevation model. However, it has been shown that this factor is very responsive to the resolution of the DEM [38]. Equation (9) is used to determine the slope length of the examined study area.

$$LS = (\frac{\lambda}{22.13})^{m} \cdot (65.41\ sin^{2}(\theta) + 4.56(\theta) + 0.065) \quad (9)$$

where:

- λ is the slope length in meters,
- θ is the slope angle in degrees,
- m is a slope length exponent that varies with slope steepness.

1. Determine the Slope Length (λ):

The slope length refers to the distance between the starting point of overland flow and the point where the slope decreases sufficiently for sediment deposition to occur or where the flow enters a designated channel.

2. The slope angle (θ) is calculated as:

The slope angle refers to the inclination of the slope surface relative to the horizontal plane. The calculation can be determined by dividing the vertical height by the horizontal distance, often known as the rise during operation.

3. The slope length (m) is calculated as follows:

The exponent (m) is dependent on the magnitude of the slope. It is commonly calculated using

$$m = \frac{\beta}{1 + \beta}$$

where β is defined as:

$$\beta = \frac{sin(\theta)}{0.0896(3.0 \, . \, sin(\theta)^{0.8} + 0.56)}$$

4. The LS factor is calculated as shown in Figure 6:

Plug the values of θ and m into the LS formula to obtain the LS factor.

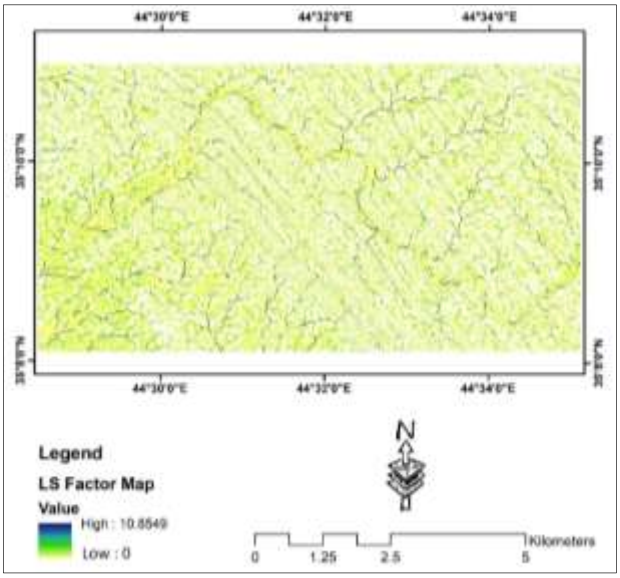

Figure 6. *Slope length factor of the study area*

2.7 Cover Management Factor

The cover-management factor (C-factor) is the most easily modifiable soil erosion risk factor that policy makers and farmers can influence to effectively decrease soil loss rates [37]. Thus, it is thought that the C-factor is the single most important decision maker concerning policy and land use as it identifies the conditions which can be regulated most effectively so as to manage the levels of erosion [37]. Obtaining the cover and management factor (C-factor) of the RUSLE is particularly challenging because to the requirement of long-term monitoring of soil erosion plots exposed to natural rainfall [4].

Specifically, land use can be described as the manner in which people use land to fulfill a specific function, while land cover refers to the physical characteristics and features commonly identify on the earth's surface, including forests, fields, crops, rocks, and deserts [16]. There are two commonly used empirical approaches to determine C-factor values in the USLE/RUSLE models. The first element, known as the C-factor, is the ratio of soil loss from land with specific vegetation cover to the loss from clean-tilled, continuously fallowed ground. The second factor, known as the C-factor, is determined by multiplying five sub-factors outlined in the RUSLE handbook [30]. The land cover is dynamic and is shaped through various natural occurrences including the reoccurring factors of drought, fire, volcanic activity, and floods [29]. Whereas, influences including cultivation, grazing, construction, and production of foods and other resources define the land utilization in the given period [16]. The values vary from nearly 0 to just above 1, exerting a significant impact on the pace at which soil is lost. It is important to carefully choose the C factor to avoid significant errors in erosion estimates. Improper selection of the C factor can lead to huge inaccuracies [45]. The land cover classes of the study area is illustrated in Figure 7. Table 2 details the C- factor values based on classes of land cover over the study region and Figure 8 states the spatial distribution of C- factor.

In this study, the land cover classes for cover management factor were extracted using Maximum Likelihood Classification Method by SNAP Program. MLC is a supervised classification technique that relies on the principles of the Bayes theorem [1]. The supervised classification method is frequently utilized and has a broad range of applications. In MLC, a pixel is classified based on its likelihood of belonging to a specific class [27]. This probability is determined by modeling the mean and covariance of the class as a normal distribution in the multispectral feature space [44].

2.8 Support Practice Factor (P)

The P factor is measured as the ratio of soil loss via a specific support practice to the associated decline with upslope and downslope cropping. The conservation practice is considered to be more efficient at reducing soil erosion when the P value is lower [35]. The value of the P factor is dependent upon the soil management practices that are linked to the slope of the region. P values vary between 0 and 1, with a value of 0 indicating a high level of artificial erosion resistance and a value of 1 indicating the complete absence of manmade erosion resistance [34]. The support practice (SP) factor (P-factor) is a crucial component in both the USLE and RUSLE models due to its major impact on mitigating soil erosion [51]. The extinction practice factor or P-factor in the USLE/RUSLE model that describes the ratio of soil loss for two different slopes is often neglected by the sub-continental soil erosion risk modeling because it is often difficult to estimate the

Table 2. *C-factor values according to land cover classes*

LC/LU type	C- factor values	Source
Crop land	0.24	[9]
Bare land	0.6	[3]
Water body	0	[6]

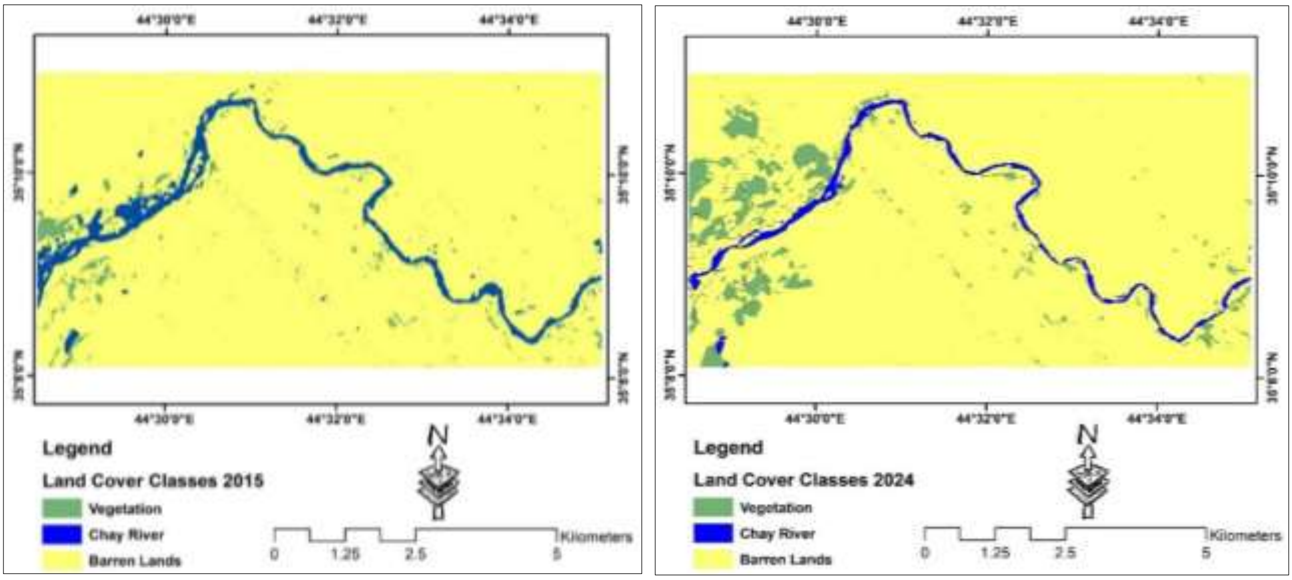

Figure 7. *Classes of land over the study area*

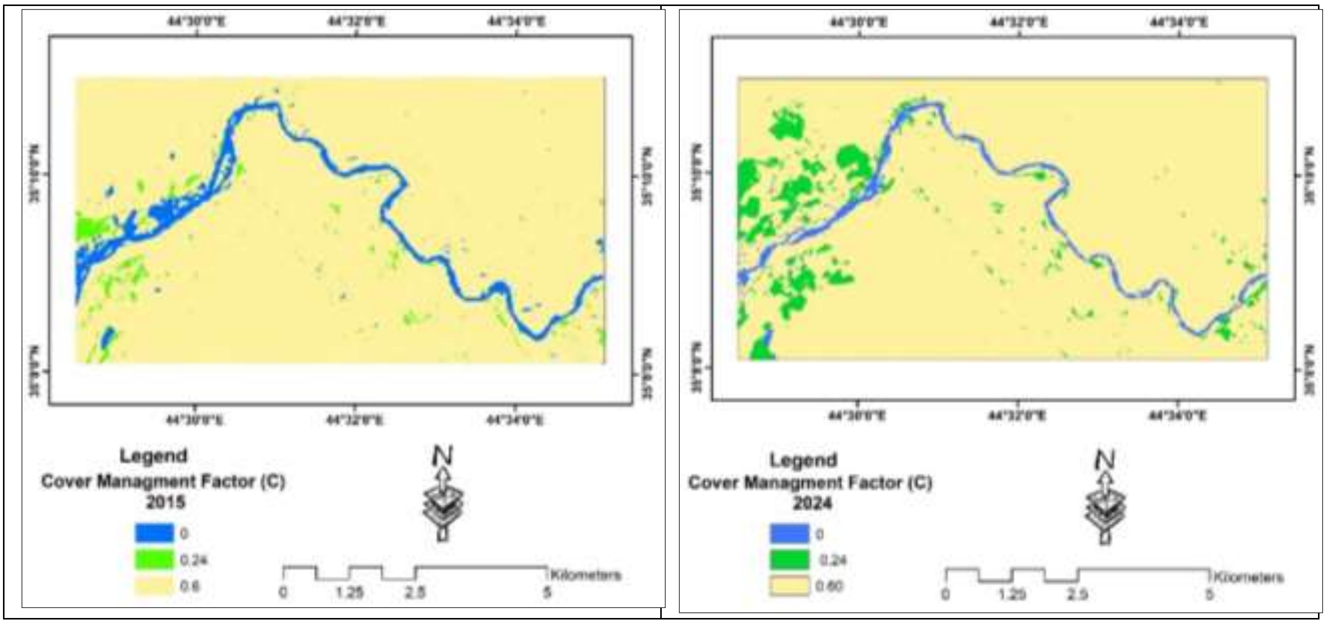

Figure 8. *Cover management factor (C) over the study area*

factor for the large region [37]. This factor is derived by measuring the ratio of soil loss because to runoff in a plot where a conservation practice has been applied to soil loss from a unit area [25].

The support practice P-factor is regarded as the most uncertain of the six RUSLE/USLE input components [37]. The Factor P encompasses methods formulated to reduce the impact of runoff by altering parameters such as concentration, velocity, besides drainage patterns and force exerted by runoff on soil [25]. The spatial values of the support practice factor are explained in Figure 9. In addition, Table 3 shows the values of the support practice factor based on the degree to which the slopes were related to the study area.

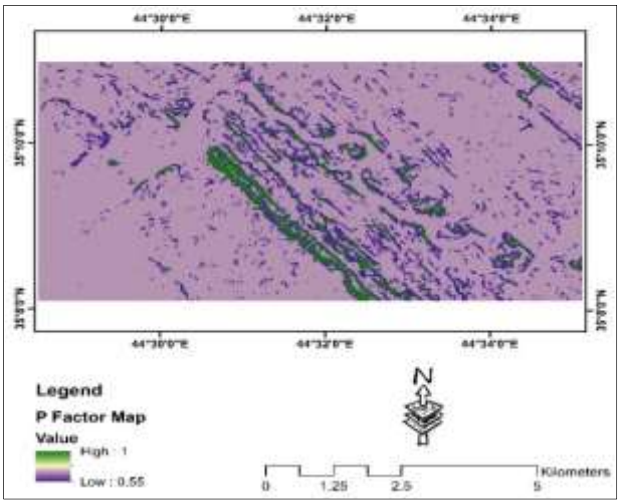

Figure 9. *Spatial distribution map of the support practice factor (P) across the study area*

Table 3. *The values of the support practice factor according to slope degree*

Slope (%)	Support practice factor (P)		
	Contouring	Crop Stripping	Terracing
0 – 7	0.55	0.27	0.1
7 – 11.3	0.6	0.3	0.12
11.3 – 17.6	0.8	0.4	0.16
17.6 – 26.8	0.9	0.45	0.18
> 26.8	1.0	0.5	0.2

3. Results And Discussion

3.1 Factors of the RUSLE Model

Rainfall runoff erosivity in the study area was classified into five categories for 2015 and 2024. The lowest rainfall values were 69.8769 and 76.5255, while the highest values were 71.3941 and 77.9954 in 2015 and 2024, respectively. This indicates that the rainfall values in 2024 are greater than those in 2015, and this discrepancy is attributed to the abundance and intensity of RRE during recent years. The soil erodibility factor over the study area was divided into two areas due to the susceptibility of soils to erosion. The first region is represented by a small part in the southwest of the study area and occupies 0.0151006%. The second area occupies a large area by % and has a value of 0.021819249. The slope length factor varies across the study area between 0 and 10.8549. The higher values are related to hilly or mountainous regions, which are more exposed to the risk of soil erosion because of the long slopes in these terrains.

The cover management factor depends entirely on the land cover of the study area. Each type of land cover has a specific cover factor. There are three main types in the study area, which are water bodies (Chai River) with a cover factor of 0 and covering areas of 2.5846 and 3.046 km^2 for 2015 and 2024, respectively. The second land cover class is vegetation cover, with a cover factor of 0.24, covering areas of 0.98 and 1.5538 km^2 for 2015 and 2024, respectively. The third and largest land cover class is barren land, which has a cover factor of 0.6, with areas of 50.04 and 49.0166 km^2 for 2015 and 2024, respectively. The support practice factor values of the study area ranged from 0.55 to 1. Higher values indicate minimum or no soil conservation measures, which leads to higher rates of soil erosion.

3.2 Soil Erosion Map 2015

Figure 10 illustrates the extent of soil erosion along the Chai River in the study area in 2015. White areas show the absence of soil loss and are scattered randomly across the study area except for regions adjacent to the river, encompassing approximately 21.443504 km^2 of the total area. Yellow areas indicate low soil erosion, nearly negligible, constituting approximately 29.31882 km^2 of the total area. Green regions, although they represent a minor proportion compared to other parameters, exhibit a widespread yet sparse distribution across the study area, occupying approximately 2.250803 km^2 of the total area. The blue regions indicate a moderate level of soil loss, surpassing the percentages of both the orange and blue categories. These areas are dispersed randomly throughout the study area, encompassing an area of 0.337952 km^2. Brown areas, which are relatively dominant in comparison to other categories, exhibit substantial or high soil loss, covering an expanse of 0.048174 km^2. Red zones represent the highest percentage of soil loss and are extensively spread across the area, with a total coverage of 0.010847 km^2. Overall, the findings indicate a significant concern regarding soil erosion within the study area, warranting prompt attention from relevant authorities.

3.3 Soil Erosion Map 2024

The final map of the extent of soil erosion along the Chai River in the study area for 2024 is shown in Figure 11. White areas indicate the absence of soil loss and are scattered randomly across the study area except for regions adjacent to the river, encompassing approximately 21.430067 km^2 of the total area. Yellow areas indicate minimal soil erosion, nearly negligible, constituting approximately 29.4398 km^2 of the total area. Green regions, although they represent a minor proportion compared to other parameters, exhibit a widespread yet sparse distribution across the study area, occupying approximately 2.15923 km^2 of the total area. The blue regions indicate a moderate level of soil loss, surpassing the percentages of both the orange and blue categories.These areas are dispersed randomly throughout the study area, encompassing an area of 0.32004 km^2. To a relative degree, they are rather dominant in opposition to the other categories, signify significant extents of soil loss, and cover an area of 0. 046423 km^2. T subsystem has the highest percentage of soil loss, disseminating through the whole area, covered the 0. 01454 km^2. In summary, pedologically, the study suggests that there is a very high risk of soil erosion the in the area of study which calls for an urgent intervention by the relevant authorities. The analysis of remote sensing images can yield both qualitative and quantitative data. measures, like error rates, to assess identification accuracy. Qualitative analysis focuses on discriminating or

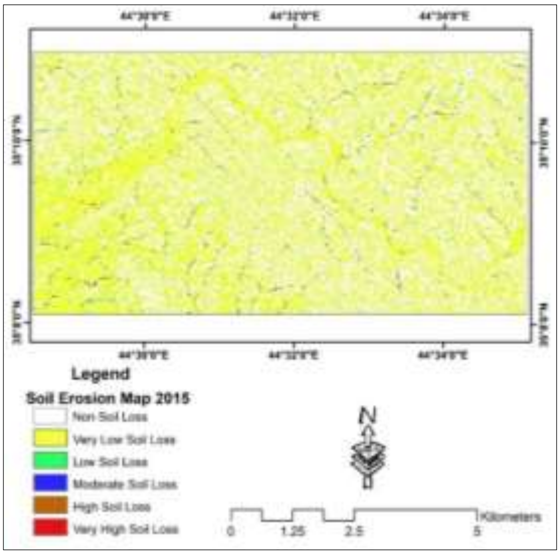

Figure 10. *Soil erosion estimation map for the study area in 2015*

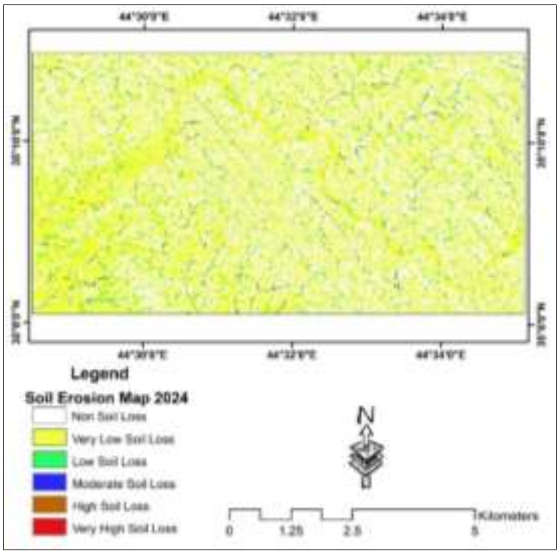

Figure 11. *Soil erosion estimation map for the study area in 2024*

recognising various materials or phenomena, whereas quantitative analysis includes gauging specific image characteristics and applying probabilistic In this reserch, the quantitative and qualitative assessment of the soil erosion of the Chai River region was done based on the RUSLE Model, with the use of GIS spatial modeling. However, the Fiqures 10 and 11 resectively, showed the results based on quantitative assessment rather than qualitative assessment due to complex area.

4. Conclusion

Soil erosion is a natural phenomenon whereby the uppermost layer of soil is displaced due to environmental forces including wind and water. Soil erosion poses substantial environmental hazards by deteriorating agricultural areas and diminishing crop yield, so adversely impacting food security and the economic livelihood of farmers. Hence, it is important to conduct a comprehensive analysis of soil erosion in the area of the Chai River, given that these areas are primarily utilized for agricultural purposes. The RUSLE model provides a simple yet effective method for assessing soil erosion. By integrating remote sensing data and GIS, it offers a reliable approach to erosion assessment. Additionally, the model incorporates satellite imagery analysis, presenting a visual representation of soil erosion patterns. The data includes information on rainfall, soil composition, land elevation, plant cover, and farming techniques. Utilizing GIS, this estimation enables us to comprehend the impact of erosion and implement appropriate approaches to mitigate it.

The findings indicated that a significant portion of the research area was susceptible to soil erosion. While the very low class exhibited the most severe degradation, with areas of 29.31882 km^2 in 2015 and 29.4398 km^2 in 2024, it still falls within the realm of soil erosion. The remaining classes of soil erosion are inferior to the very low class, and very high soil erosion is documented in an estimated area of 0.010847 km^2 in 2015 and 0.01454 km^2 in 2024. Meanwhile, the results recommend the use of high-resolution images for such study that require a level of detail of the soil ersoin. Ultimately, our methodology for assessing soil eroision can lead to a deeper understanding of the phenomena, in other areas and for other types of applications.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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