SOIL EROSION ESTIMATION FROM SATELLITE USING ADVANCED STATISTICAL LEARNING

Project-2024

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Abstract

Soil erosion is a pervasive environmental issue with significant implications for land productivity, water quality, and ecosystem health. This study focuses on the estimation of soil erosion using satellite imagery and advanced statistical learning techniques, with a particular emphasis on the Kheda district, spanning an area of 719,400 hectares in India.

The introduction highlights the global significance of soil erosion as a form of land degradation and its adverse impacts on sustainable development goals. Various soil erosion models, including empirical and process-based approaches, are discussed, with a spotlight on the Revised Universal Soil Loss Equation (RUSLE) model due to its widespread acceptance and compatibility with remote sensing and GIS.

The literature review explores key studies and findings related to soil erosion assessment methodologies, remote sensing, GIS integration, and the application of advanced statistical learning techniques. Empirical and process-based models, remote sensing data sources, and machine learning algorithms are discussed in the context of their contributions to soil erosion estimation and management.

In this study, satellite imagery is utilized to derive essential input parameters for the RUSLE model, such as land cover, slope, NDVI, soil and rainfall data.

The methodology section outlines the step-by-step process of data acquisition, preprocessing, model implementation, and analysis. The study area, Kheda district, is described in terms of its geographical characteristics, including its area, location, and altitude.

By leveraging satellite imagery and advanced statistical learning techniques, this study aims to provide a comprehensive assessment of soil erosion dynamics in Kheda district. The findings will contribute to a better understanding of soil erosion processes and support informed decision-making for sustainable land management practices and conservation efforts in the region.

Acknowledgment

We express our sincere gratitude to all those who have contributed to the completion of this study on soil erosion estimation using satellite imagery and advanced statistical learning techniques.

First and foremost, we extend our deepest appreciation to Mr. Justin George K and Mr. Prabhakar Alok Verma, for their invaluable guidance, support, and encouragement throughout this research endeavour. Their expertise and mentorship have been instrumental in shaping the direction and methodology of our study.

We would also like to thank Dr. NR Patel and Mr. Abhishek for their coordination and assistance as course coordinators. Their dedication to facilitating our academic pursuits has been greatly appreciated.

Furthermore, we acknowledge the contributions of our colleagues and peers who have provided assistance, feedback, and encouragement during the course of this project. Their collaboration has enriched our learning experience and contributed to the success of this study.

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1. Introduction

Soil erosion, the most dominant form of land degradation is affecting the quality of various natural ecosystems including aquatic environments and crop production due to its various prominent onsite and offsite effects (Montanarella et al. 2016). Due to the intensity and vast spatial extend, it has been identified as one of the predominant hindrances in achieving the goal of sustainable development, by Rio+20 conference parties (United Nations, 2012). The constructive process of natural geologic erosion determined by different environmental factors, when accelerated by various anthropogenic activities has led to an estimated annual soil loss of 20-30GT globally, through water erosion only (Renard et al., 1997; FAO and ITPS 2015). High average soil erosion rates in the range of 30–40 t ha−1 yr−1 have been reported from the various agroecosystems in Asia, Africa and South America; with about 6.6 billion tonnes of soil reported to be lost from India annually (Pimentel, 2006).

The complications and non-feasibility regarding wide spread measurement of soil erosion rates at large spatial extents has necessitated the adoption of various soil erosion models including empirical, semi-empirical as well as physically/process-based models (Jetten et al., 2003; Karydas et al., 2014). Various models including the empirical - USLE (Universal Soil Loss Equation), AGNPS (Agricultural Nonpoint Source Model), RUSLE (Revised Universal Soil Loss Equation), CREAMS (Chemical Runoff and Erosion from Agricultural Management Systems), MUSLE (Modified Universal Soil Loss Equation); semi-empirical – AnnAGNPS (Annualized Agricultural Non-Point Source), SWAT (Soil and Water Assessment Tool), HSPF (Hydrologic Simulation Program Fortran); physical – LISEM (Limburg Soil Erosion Model), WEPP (Watershed Erosion Prediction Project), EUROSEM (European Soil Erosion Model) and many others differing in terms of processes considered, complexity as well as data requirement has been widely used by researchers for predicting soil erosion rates at different scales (Karydas et al., 2014). Even though the physical based models are known for their better performance, their large input data requirement (with high spatial resolution), increased complexities and high computation cost has made the adoption of empirical models much common among researchers as well as policy makers. Among these, RUSLE model has gained exceptional popularity and acceptance worldwide for erosion risk assessment at different scales including field (Shrestha., 1997; Maetens et al., 2012), watershed (Prasannakumar et al., 2012; Pan and Wen., 2014; Mhangara et al., 2012), as well as catchment or regional scales (Lu et al., 2003; Mandal and Sharda, 2013; Panagos et al., 2015a; Uddin et al., 2016). This could be attributed to its modest data requirements, robust/easily understandable model structure as well as compatibility with remote sensing and GIS, especially in regions where the applicability of many other complex models are limited due to inability to meet high input data requirements and costs (Lal et al., 1997; Galdino et al., 2016). Even though RUSLE does not consider transportation/deposition of the sediments and predicts only long-term average annual erosion, the outputs have globally been well accepted for identifying high erosion risk/vulnerable areas (Uddin et al., 2016; Thomas et al., 2018).

For our study, we focus on soil erosion estimation from satellite imagery using advanced statistical learning techniques, with a specific emphasis on the Kheda district. In this study, we aim to leverage satellite imagery and advanced statistical learning methods to estimate soil erosion in Kheda district, utilizing the RUSLE model as the primary tool. By doing so, we seek to contribute to a better understanding of soil erosion processes and patterns in the region, facilitating informed decision-making for sustainable land management and conservation efforts.

2. Literature Review

Soil erosion, as a widespread phenomenon, has garnered significant attention from researchers across various disciplines. In this literature review, we delve into key studies and findings pertaining to soil erosion assessment, focusing on methodologies, models, and applications, particularly in the context of satellite imagery and advanced statistical learning techniques.

Numerous soil erosion models have been developed to estimate erosion rates at different spatial scales. Among these, empirical models such as the Universal Soil Loss Equation (USLE) and its revised version (RUSLE) have been widely employed due to their simplicity and ease of application (Renard et al., 1997). These models incorporate factors such as rainfall erosivity, soil erodibility, slope length and steepness, cover management, and erosion control practices to predict soil loss. While empirical models provide valuable insights, they often lack the ability to capture complex processes accurately.

Process-based models, on the other hand, simulate erosion processes using physical principles and detailed parameterizations. Models like the Soil and Water Assessment Tool (SWAT) and the Watershed Erosion Prediction Project (WEPP) offer more mechanistic representations of erosion dynamics, making them suitable for detailed studies but requiring extensive input data and computational resources (Neitsch et al., 2011; Arnold et al., 1998).

The integration of remote sensing and Geographic Information Systems (GIS) has revolutionized soil erosion assessment by providing spatially explicit data and analytical tools. Satellite imagery offers a valuable source of information for mapping land cover, land use, and terrain characteristics, which are essential inputs for soil erosion models (Lal et al., 1997). Remote sensing techniques, including optical, radar, and LiDAR sensors, enable the monitoring of land surface changes and the identification of erosion-prone areas with high spatial and temporal resolution

3.Description of Study Area

For our study on soil erosion estimation from satellite using advanced statistical learning, we have selected the Kheda district as our study area. Kheda district covers an extensive area of 719,400 hectares (3953 square kilometres) and is situated at coordinates 72.68° E longitude and 22.75° N latitude.

Furthermore, the study area exhibits an altitude ranging from 20 to 25 meters above mean sea level, contributing to its varied topography and terrain features. Understanding the spatial distribution of soil erosion within such a dynamic landscape is essential for effective land management and conservation efforts.

By focusing our research on the Kheda district, we aim to gain insights into the patterns, trends, and drivers of soil erosion using satellite imagery and advanced statistical learning techniques.

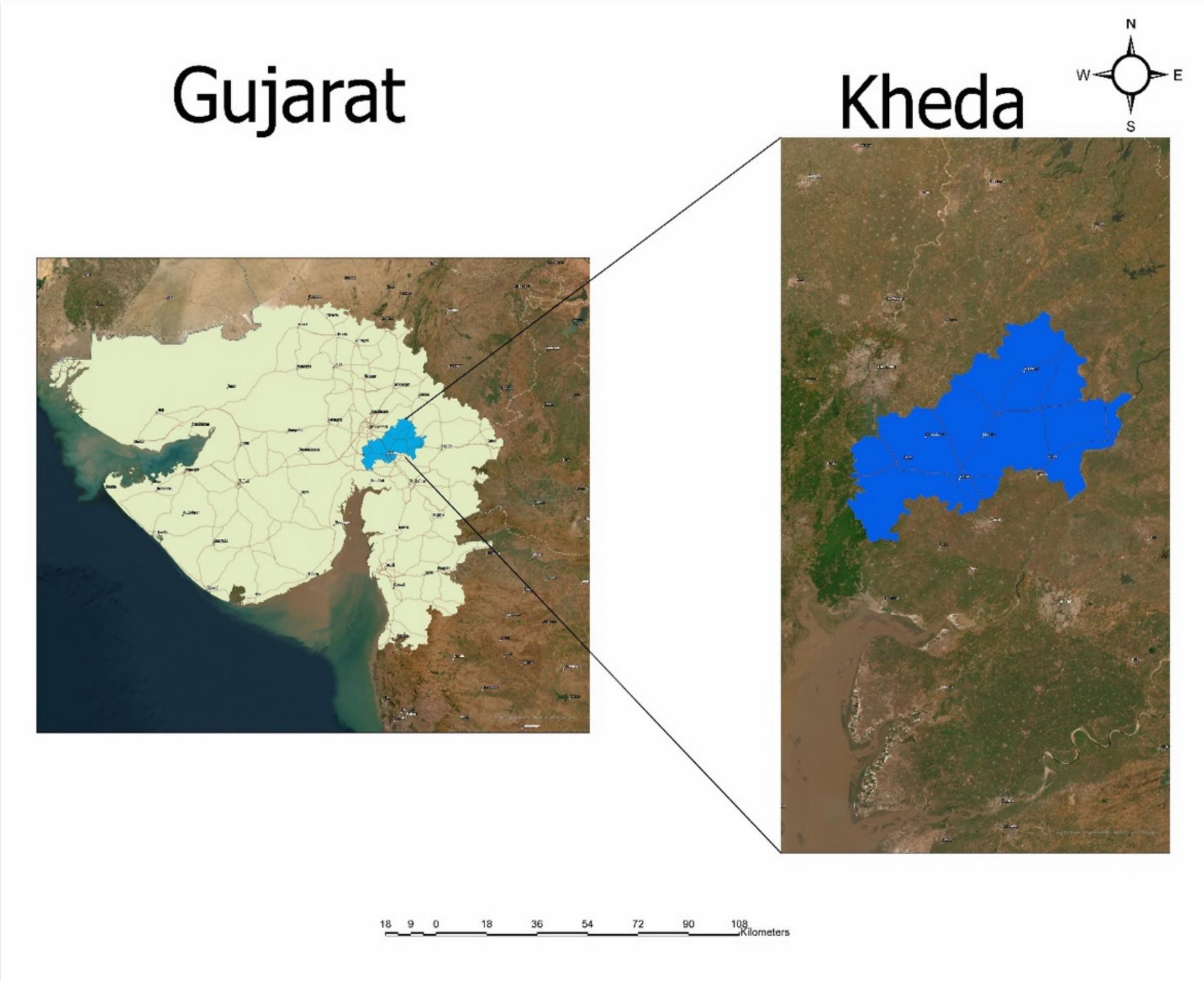

Fig.1. Image of Study area

4. Materials and methods

4.1. Data used

Various remote sensing data derived thematic and auxiliary data were used in this study. The Digital Elevation Model (DEM) data was downloaded from the USGS Earth Explorer data portal and producing the layer of topographic factor(https://developers.google.com/earthengine/datasets/catalog/USGS_SRTMGL1_003).The LULC data was obtained from Esri Land Cover website(https://livingatlas.arcgis.com/landcover/) .The R factor data was downloaded from the European Soil Data Centre (ESDAC) website at (https://esdac.jrc.ec.europa.eu). The soil grids of various depths (0 cm, 5 cm, 15 cm, and 30 cm) were downloaded from the website at (https://data.isric.org) and producing layer of K factor.

Data	Data Item	Type	Source
Geology	Geology map & information	Shape file	Bhukosh website
Digital Elevation Model	Raster Map (30m resolution)	Raster file	USGS Earth Explorer data portal
Land use land cover	Land use classes (10m resolution)	Raster file	Esri Land Cover website
Soil Texture	Soil physical and chemical properties (250m resolution)	Raster file	SoilGrids 250
Normalized difference vegetation index	Raster Map (10m resolution)	Raster file	Google Earth Engine

Table 1. Data used.

4.2. Soil erosion mapping using RUSLE model

Revised Universal Soil Loss Equation (RUSLE) model was used to predict soil loss in the study area. The RUSLE model was developed as an empirical model representing the main factors controlling soil erosion, namely climate, soil, topography, and land cover management. For erosion risk assessment and conservation planning, especially for large area like Uttarakhand state, RUSLE model is most appropriate. RUSLE model has been widely accepted and globally used by researchers in various countries at regional scale (Lu et al., 2003; Panagos et al., 2015a; Yang et al., 2018), representing diverse topographic conditions. In RUSLE, erosion is seen as a product of rainfall erosivity (the R factor, which equals the potential energy); this multiplies the resistance of the environment, which comprises K (soil erodibility), LS (the topographical factor), C (vegetation cover and farming technique) and P (conservation practices factor). Detailed description regarding the model computations and equations are described by Renard et al. (1997). The RUSLE model could be summarized as Eq. 1, as given below.

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

Where, A = Average annual soil erosion (t ha−1 yr−1), R= Rainfall erosivity factor (MJ mm ha−1 h−1 yr−1), K = Soil erodibility factor (t ha h ha−1 MJ−1 mm−1), LS= Slope -length and slope-steepness factor (dimensionless), C = Crop management factor (dimensionless) and P = Conservation practice factor (dimensionless).

4.2.1. Methodology

- Data Acquisition: Downloading relevant datasets from Google Earth Engine.
- Factor Calculation: Utilizing Google Earth Engine to calculate the factors required by the RUSLE model. These factors typically include rainfall erosivity, soil erodibility, slope length and steepness, cover management, and erosion control practices.
- Map Creation: Generating maps representing each factor of the RUSLE model within the GIS environment. This step involves visualizing the spatial distribution of factors across the study area.
- Soil Erosion Calculation: Employing the RUSLE model in Google Earth Engine to calculate soil erosion rates based on the integrated datasets and factors.
- Spatial Analysis: Calculating the mean soil erosion for each taluka (sub-district) within Kheda district using Google Earth Engine. This step involves aggregating the calculated erosion rates to a higher geographical level for analysis and interpretation.

By following these steps, the study aims to comprehensively assess soil erosion patterns and trends within the Kheda district.

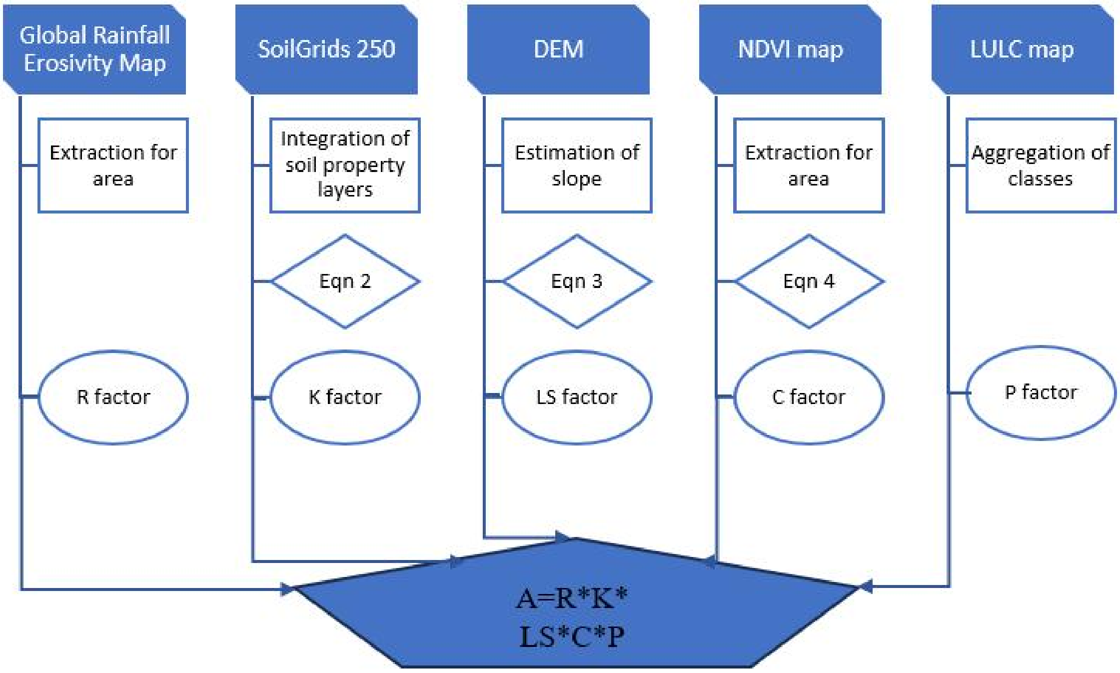

Fig. 2. Flow chart of the methodology adopted for soil erosion assessment using RUSLE modelling.

4.2.2. Rainfall erosivity factor (R – factor)

R factor is a quantitative measure of the erosive power of rainfall. It measures the ability of a rainfall to cause detachment and transportation of soil particles. The kinetic energy of the rainfall, which is highly influenced by the rainfall intensity, duration as well as volume, determines the erosivity. This can be computed for a single storm or a series of storms within a specific period to account for cumulative rainfall erosivity. Due to the scarcity of high temporal resolution data for erosivity estimation in major parts of the study area, we used the Global erosivity map at 30 arc-seconds (~1 km) resolution prepared and made freely available by European Soil Data Centre (ESDAC) in their website at http://esdac.jrc.ec.europa.eu. The global erosivity map was generated from a Global Rainfall Erosivity Database (rainfall erosivity estimated for 3625 stations covering 63 countries located in diverse climatic zones) using a Gaussian Process Regression (GPR) based spatial interpolation

(Panagos et al., 2017). The database included rainfall erosivity estimated for 247 rainfall stations of India situated at various locations, associated with Indian Meteorological Department. The global erosivity map was obtained and the values for the spatial extent of study area was extracted for further use.

➢ Soil physical and chemical properties

Clay: Clay particles are tiny and have a high surface area, which gives them strong cohesion. This cohesion helps clay soils retain water and resist erosion by holding soil particles together. However, when clay soils become saturated with water, they can become extremely sticky and prone to surface sealing, which impedes water infiltration and increases runoff and erosion.

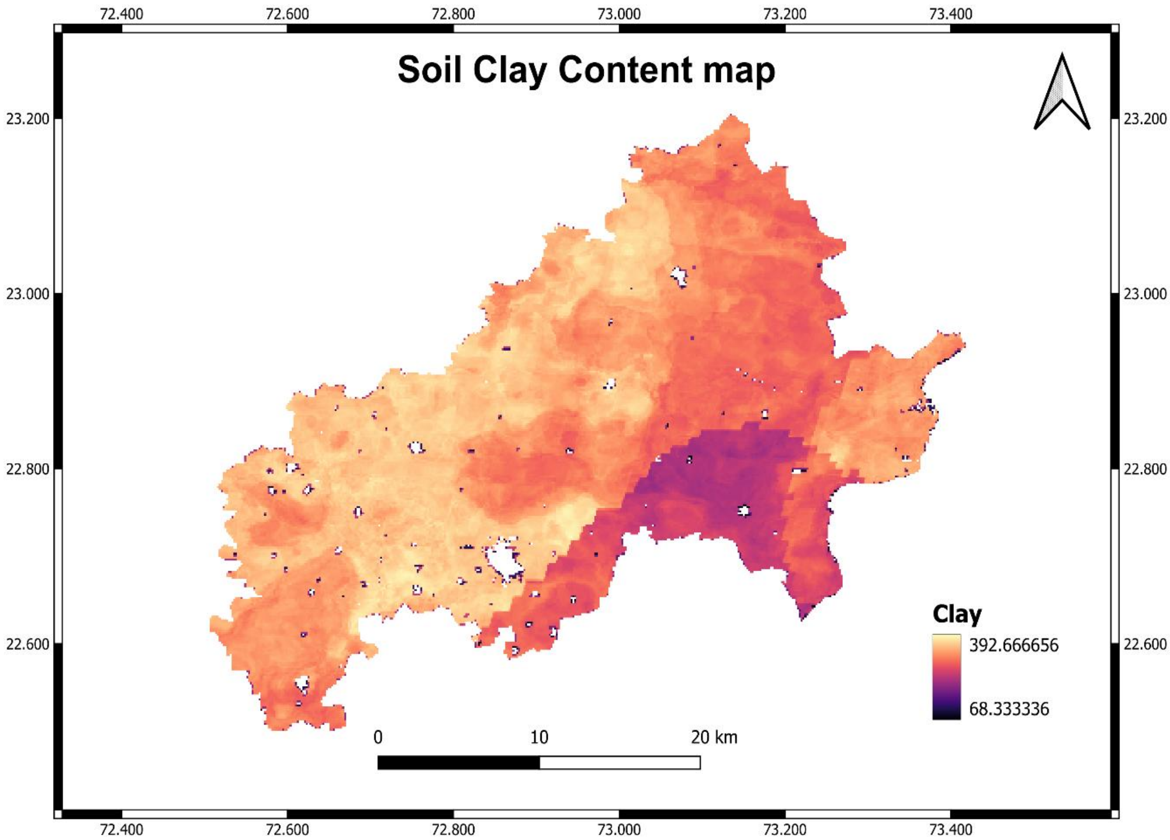

Fig. 3. Clay content in the area.

Sand: Sand particles are larger than clay particles and have low cohesion. As a result, sandy soils are more susceptible to erosion by wind and water. They have poor water-holding capacity and tend to drain quickly, leading to increased runoff during rainfall events. Without vegetation or other forms of soil cover, sandy soils can be easily displaced and transported by wind or water erosion.

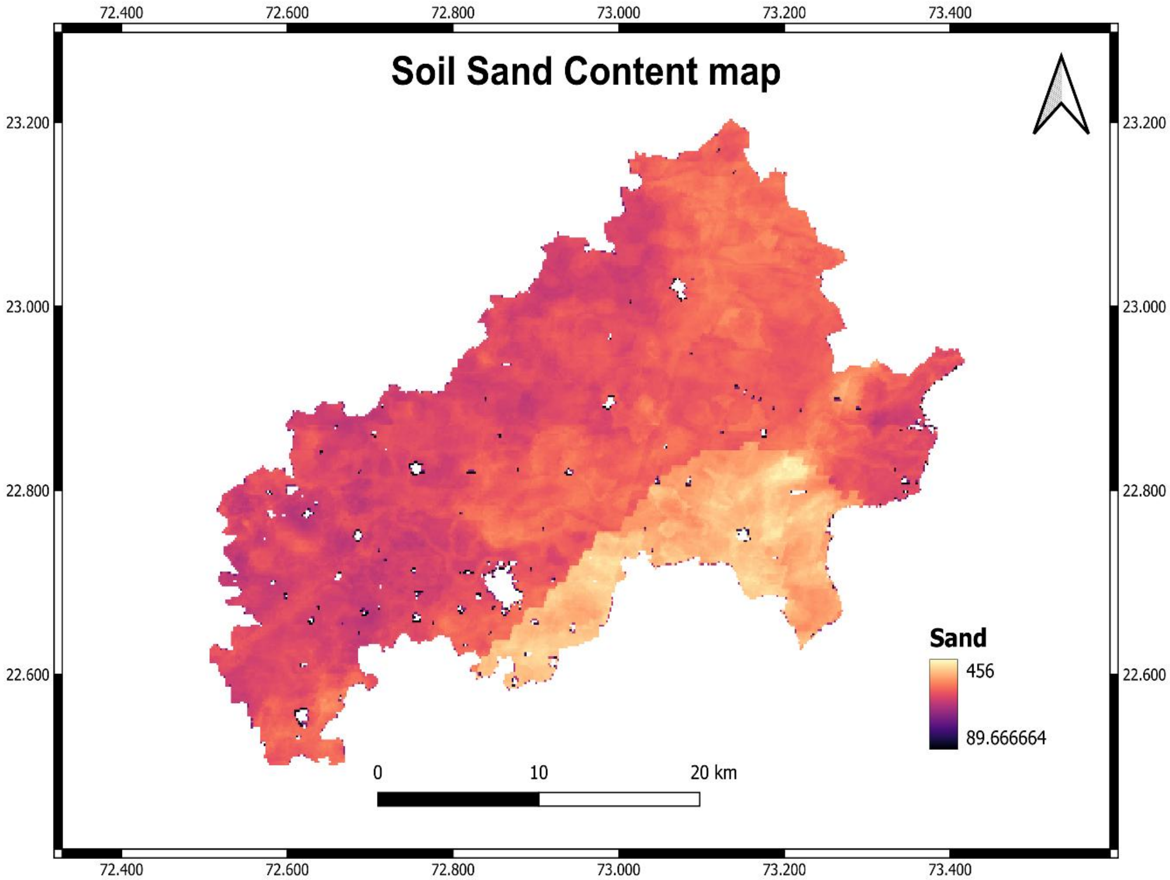

Fig. 4. Sand content in the area.

Silt: Silt particles fall between clay and sand in size and have moderate cohesion. Silty soils have good water retention capacity and are less prone to surface sealing compared to clay soils. However, they can still be susceptible to erosion, especially when left bare or exposed to intense rainfall events. Silt soils are commonly found in floodplains and areas with periodic inundation.

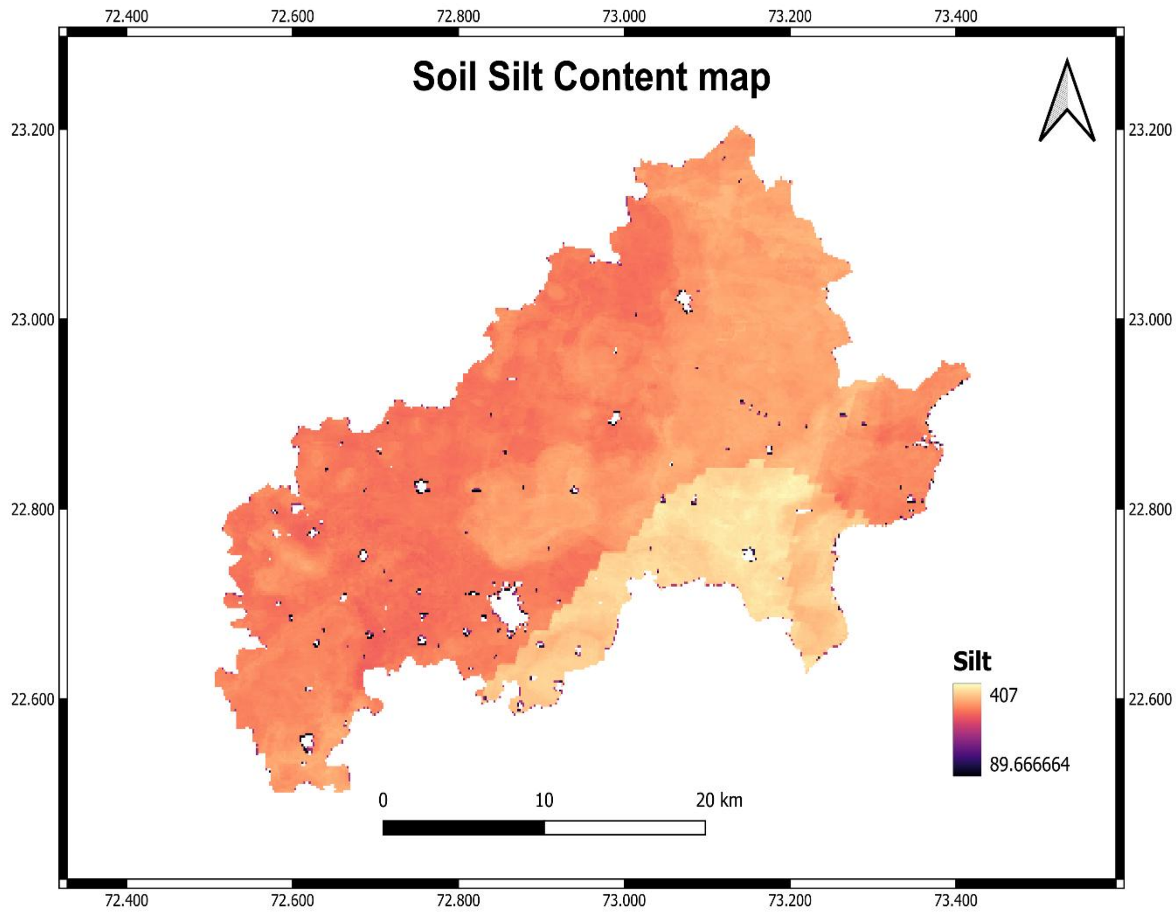

Fig. 5. Silt content in the area.

Organic Carbon: Soil organic carbon is derived from decaying plant and animal matter and plays a vital role in soil structure, fertility, and erosion resistance. Soils with higher organic carbon content tend to have better aggregation, water infiltration, and moisture retention properties, which help reduce erosion by stabilizing soil structure. Organic carbon also acts as a binding agent, holding soil particles together and preventing detachment and transport by wind and water.

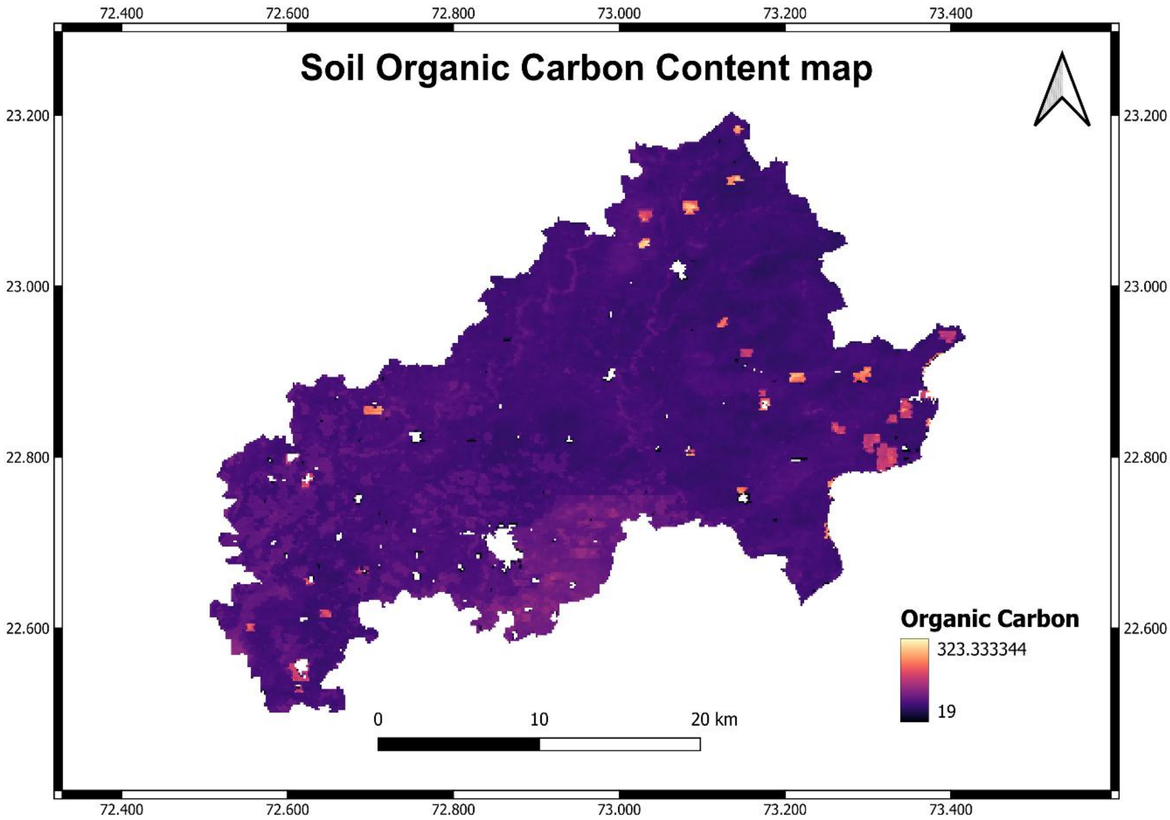

Fig. 6. Organic Carbon content in the area.

4.2.3. Soil erodibility factor (K –Factor)

The K factor represents the susceptibility of different soils to erosion, determined under standard unit plot conditions for both amount and rate of runoff (Bryan, 2000). Various soil characteristics such as primary particle size, porosity, water retention forces, permeability, infiltration rate, structural integrity, organic matter content etc are found to influence inherent nature of various soils to erode or resist erosion. Due to the large spatial extent of the study area and mountainous terrain, the scope for detailed soil survey was highly restricted. Therefore, we used the soil data layers obtained from SOILGRIDS250m for the computation of K factor. EPIC model equation based on contents of sand, silt, clay and organic carbon was used for the estimation of K factor (Sharpley and Williams, 1990). Similar approach of K factor estimation for soil erosion modelling (using RUSLE model) was adopted by other researchers too (Yang et al., 2018).

The following equation was used for the computation of K factor.

$$K = 0.1317 * \left(0.2 + 0.3 * e^{\left[-0.0256*SAN\left(1 - \frac{SIL}{100}\right)\right]} * \left(\frac{SIL}{CLA+SIL}\right)^{0.3}\right) * \left[1 - \frac{0.25*TOC}{TOC+e^{(3.72-2.95*TOC)}}\right] * \left[1 - \frac{0.7*SN_1}{SN_1+e^{(22.9*SN_1-5.51)}}\right] \quad (2)$$

Where, K is soil erodibility factor (t ha h ha−1 MJ−1 mm−1), SAN is sand weight content (%), SIL is silt weight content (%), CLA is clay weight content (%), TOC is soil organic carbon content (%), SN1=1 – (SAN / 100).

SOILGRIDS250m is a gridded soil information, which provides global predictions for various standard numeric and categorical soil properties for seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm) at 250 m resolution. The global predictions were based on digital soil mapping concept utilizing a global soil profile database (~150,000 soil profiles) and stack of remote sensing-based soil covariates, fitted using an ensemble of machine learning techniques (Hengl et al., 2017). The SOILGRIDS hosted by International Soil Reference and Information Centre (ISRIC) can be freely downloaded from www.soilgrids.org. For estimation of K factor for 0–30 cm depth, we need to get the average value of different soil parameters (sand, silt, clay and organic carbon content) for the 0–30 cm depth interval. Average soil property values of 0–30 cm depth interval was obtained by estimating a weighted average of the different depth predictions (0, 5, 15 and 30 cms) using a trapezoidal rule based numerical integration as described in Hengl et al. (2017).

- **Digital Elevation Model (DEM)**

A digital elevation model (DEM) serves as a fundamental tool in soil erosion projects, offering a precise depiction of terrain elevation and slope characteristics in digital form. DEM analysis identifies erosion hotspots by assessing slope gradients, with steeper slopes typically indicating higher erosion risk due to gravitational forces.
Sophisticated erosion models like the Universal Soil Loss Equation (USLE) utilize DEM-derived parameters to predict erosion rates, incorporating factors such as slope, soil type, land cover, and rainfall intensity.

The insights garnered from DEMs facilitate the strategic planning of erosion control measures, including terracing, contour plowing, and vegetative buffers. By aligning these measures with terrain characteristics revealed by the DEM, their effectiveness can be maximized.

Furthermore, DEMs enable the monitoring of landscape changes over time, providing valuable feedback on the success of erosion control efforts and guiding adaptive management strategies for long-term soil conservation.

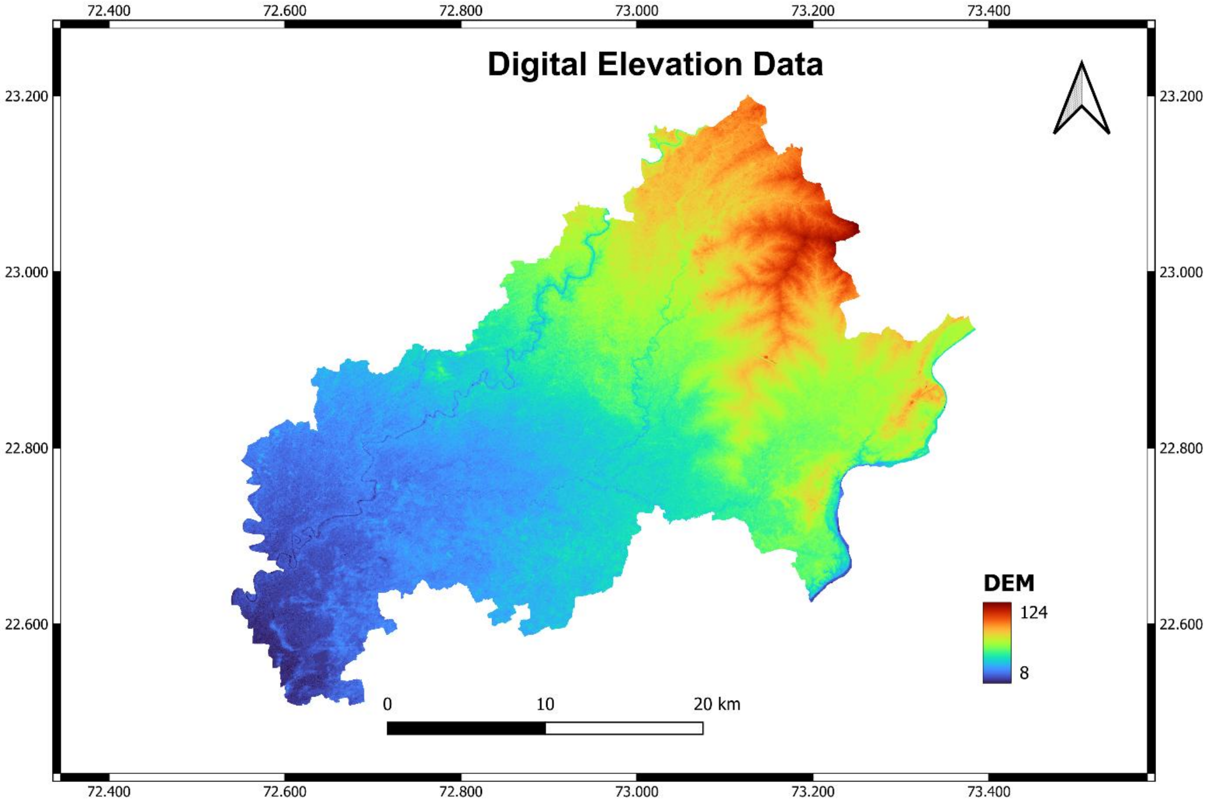

Fig. 7. Digital Elevation Model (DEM) of the Area.

4.2.4. Slope length (L) and steepness (S) factor (LS factor)

Topography is considered as the most important factor determining the rate of erosion. The influence of topography is characterized in the form of slope length (L) and slope steepness (S) factors, as erosion is not only governed by uninterrupted length of slope but also by its steepness. The LS factor is dimensionless with values equal to or greater than zero and is estimated as the ratio of soil loss from a field of certain slope length and steepness to that from the standard RUSLE plot having unit plot length (22.13 m) and steepness (9%) with all the other soil conditions remaining the same (Renard et al., 2011). Various researchers (Wischmeier and Smith. 1978; McCool et al., 1987; Renard et al., 1997; Desmet and Govers, 1996; Liu et al., 2002) have adopted different methods for estimation of LS factor under diverse topographical conditions using field-based measurements as well as quantitative measurement of earth's surface in the form of digital elevation models. The LS factor, derived from a Digital Elevation Model (DEM), was calculated specifically using (Eq. 3).

$$LS = (\text{flow acc.} \times \text{map resolution}/22.13)^{0.5} \times (\sin \text{slope}/0.0896)^{1.4} \quad (3)$$

where flow acc. is the accumulated slope effect on soil erosion, map resolution is the grid size of the map, and sin slope is the slope degree of land in sin.

- **Normalized Difference Vegetation Index (NDVI)**

Remote sensing techniques are employed for monitoring and mapping condition of ecosystems of any part of earth. Vegetation cover is the one of most important biophysical indicator to soil erosion. Vegetation cover can be estimated using vegetation indices derived from satellite images. Vegetation indices allow us to delineate the distribution of vegetation and soil based on the characteristic reflectance patterns of green vegetation. The Normalized Difference Vegetation Index (NDVI), one of the vegetation indices, measures the amount of green vegetation. The spectral reflectance difference between Near Infrared (NIR) and red is used to calculate NDVI.

The formula can be expressed as (Jensen, 2000);

NDVI = (NIR – red) / (NIR + red)

The NDVI has been used widely in remote sensing studies since its development (Jensen, 2005). NDVI values range from -1.0 to 1.0, where higher values are for green vegetation and low values for other common surface materials. Bare soil is represented with NDVI values which are closest to 0 and water bodies are represented with negative NDVI values (Lillesand et al., 2004: Jasinski, 1990; Sader and Winne, 1992). More than 20 vegetation indices have been proposed and used at present. Since NDVI provides useful information for detecting and interpreting vegetation land cover it has been widely used in remote sensing studies (Gao, 1996: Myneni and Asrar, 1994; Sesnie et al., 2008).

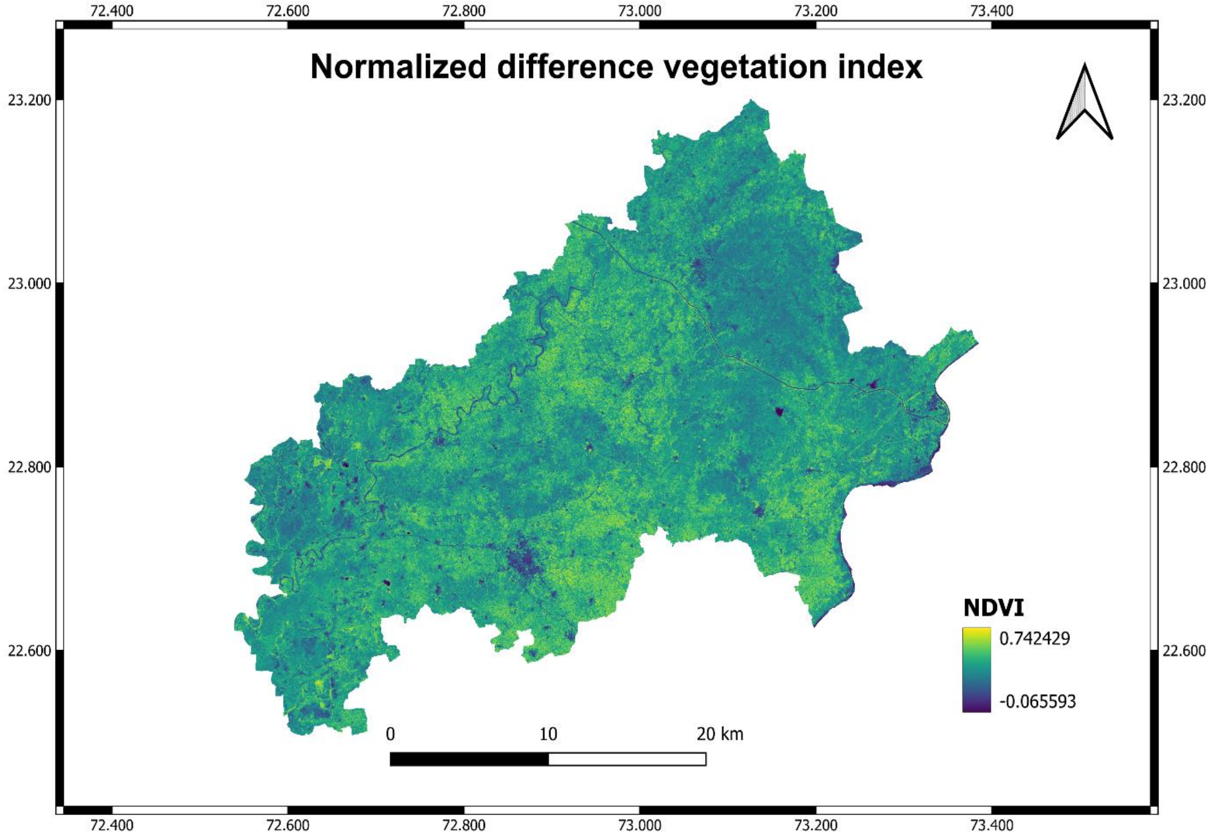

Fig. 8. Normalized Difference Vegetation Index (NDVI) of the Area.

4.2.5. Cover management factor (C)

The C-factor represents the effect of soil-disturbing activities, plants, crop sequence and productivity level, soil cover and subsurface bio-mass on soil erosion. It is defined as the ratio of soil loss from land cropped under specific conditions to the corresponding loss from clean-tilled, continuous fallow (Wischmeier and Smith, 1978). Currently, due to the variety of land cover patterns with spatial and temporal variations, satellite remote sensing data sets were used for the assessment of C-factor (Karydas et al., 2009, Tian et al., 2009). The Normalized Difference Vegetation Index (NDVI), an indicator of the vegetation vigor and health is used along with the following formula (eq. 4) to generate the C-factor value image for the study area (Zhou et al., 2008, Kouli et al., 2009).

$$C = \exp\left[-\alpha \frac{\text{NDVI}}{(\beta - \text{NDVI})}\right] \tag{4}$$

where α and β are unitless parameters that determine the shape of the curve relating to NDVI and the C-factor. Van der Knijff et al. (2000) found that this scaling approach gave better results than assuming a linear relationship and the values of 2 and 1 were selected for the parameters α and β, respectively. This equation was successfully applied for assessing the C-factor of areas with similar terrain and climatic conditions (Prasannakumar et al., 2011a, Prasannakumar et al., 2011b). The C-factor in the present case ranges between 0.3 and 1.5.

- **Land Use Land Cover (LULC)**

Land use refers to the human activities and purposes for which land is utilized, including residential, commercial, agricultural, industrial, recreational, and conservation purposes. It encompasses the various ways in which people interact with and modify the land to meet their needs and aspirations.

Land cover, on the other hand, describes the physical attributes and surface characteristics of the land, such as forests, grasslands, wetlands, water bodies, urban areas, and bare soil. It focuses on the biophysical features that occupy the land surface, regardless of whether they are natural or man-made.

Both land use and land cover are essential for understanding and managing landscapes, as they provide insights into patterns of human activity, ecological processes, and environmental changes over time. Analysis of LULC patterns helps in urban planning, natural resource management, biodiversity conservation, climate change assessment, disaster risk reduction, and sustainable development.

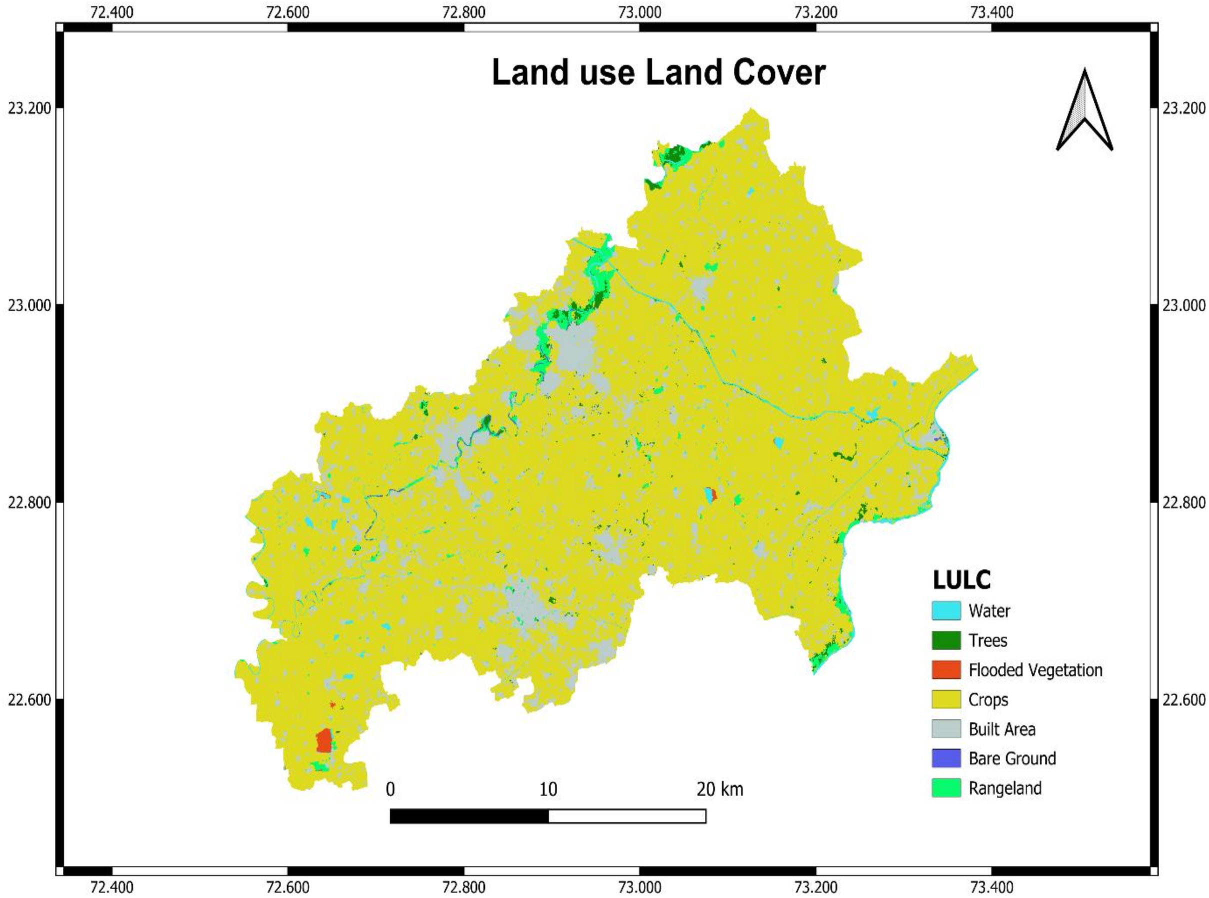

Fig. 9. Land Use Land Cover (LULC) of the Area.

4.2.6. Conservation practice factor (P factor)

P factor is also commonly referred to as support practice factor and is defined as the ratio of soil erosion under a specific soil conservation practice to the corresponding loss under a condition of up and down tillage as well as cultivation in slopes (Wischmeier and Smith, 1978). It reflects the effects of various conservation and support practices in reducing soil erosion by influencing velocity, concentration as well as direction of runoff and hydraulic forces acting on soil (Renard et al., 1997). The P factor summarizes the overall effect of all those management practices such as strip cropping, contour farming, ridge planting, terracing, bunding etc on reducing the rate as well as volume of runoff and thus eventually soil erosion rates. The value of P factor decreases wherever these practices are adopted and results in increased deposition of sediments at hill slope surfaces. Remote sensing image classificationbased techniques in combination with expert knowledge, literature-based P value estimation as well as empirical equation-based P factor approximation are the different methods adopted by researchers (Terranova et al., 2009; Karydas et al. 2009; Wischmeier and Smith, 1978; Renard et al., 1997; Foster et al., 2008).

In this study we used an approach involving LULC map of the area, where P factor was assigned to different land cover classes based on literature survey of works conducted in large areas with similar characteristics as well as expert opinion (Jena et al., 2018; Panagos et al., 2015d). The finalized P values were assigned to different LULC classes and reclassified to yield P factor maps of the entire study area.

5. Results and discussion

5.1. Rainfall erosivity factor (R – Factor)

The study area for this research is Kheda district in Gujarat. The rainfall erosivity factor, obtained from the Global Rainfall Erosivity Database, ranged from 3161.59 to 3340.72 MJ mm ha−1 h−1 yr−1 at a spatial resolution of 30 arc-seconds. The mean R factor value observed in the area was 3251.16 MJ mm ha−1 h−1 yr−1. This value exhibited a subtle gradient pattern from west to east across the district.

The higher values of the R factor were concentrated in the central and eastern parts of Kheda district, aligning with regions of slightly higher elevation and potential for more intense rainfall events. The lower R factor values were observed in the western and northern areas, which are characterized by lower elevations and more arid conditions.

These observations suggest that rainfall erosivity in Kheda district is influenced by the geographic and topographic features of the region, with varying degrees of intensity depending on the location within the district. This pattern is consistent with regional climatic variations and their impact on erosivity.

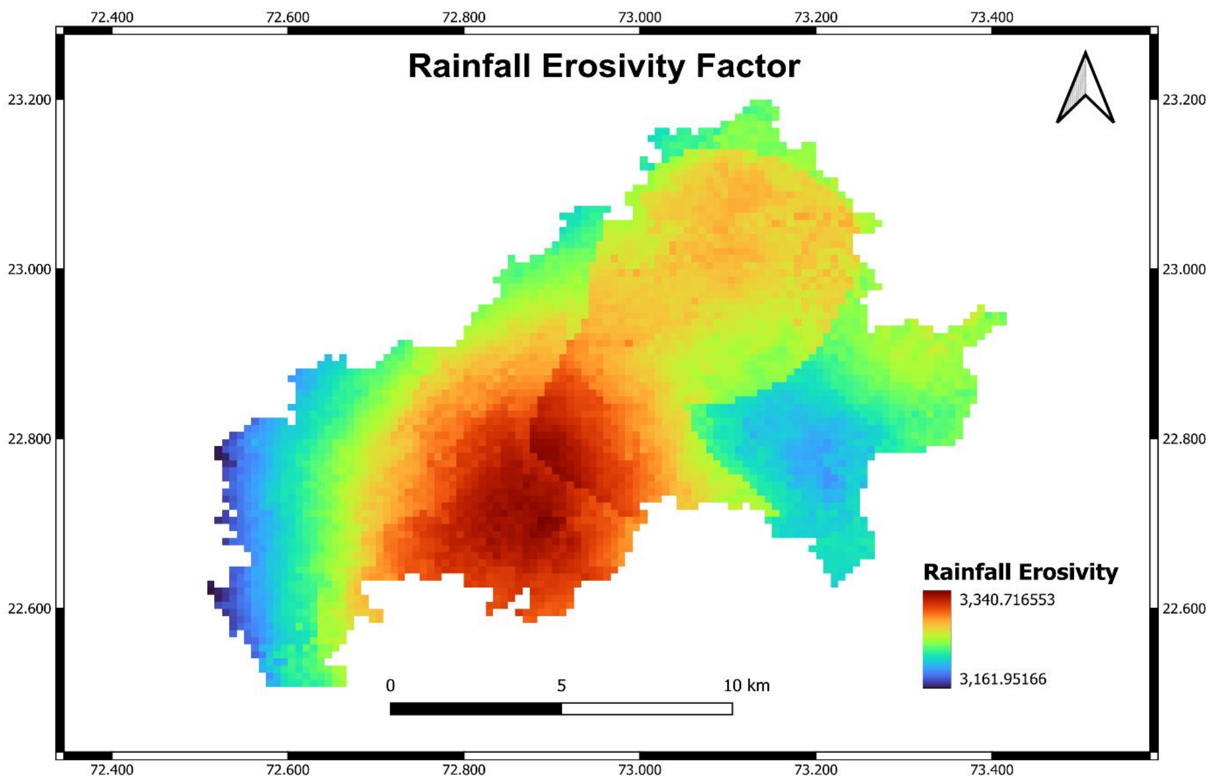

Fig. 10. Rainfall Erosivity factor the area.

5.2. Soil erodibility factor (K –factor)

In the study area of Kheda district in Gujarat, the soil erodibility factor was estimated using SOILGRIDS data with the EPIC model equation. The values ranged from 0.029 to 0.051, with a mean value of 0.04 across the entire district. Soil erodibility was found to be relatively low in areas with denser vegetation and higher soil organic carbon content, particularly in the southern and eastern parts of Kheda district.

These lower erodibility values in these regions can be attributed to the protective effects of organic matter and vegetation cover on soil stability, as well as the moderating influence of the climate in those areas. This suggests that the erosion risk in Kheda district may be more pronounced in regions with lower organic carbon content and less vegetative cover.

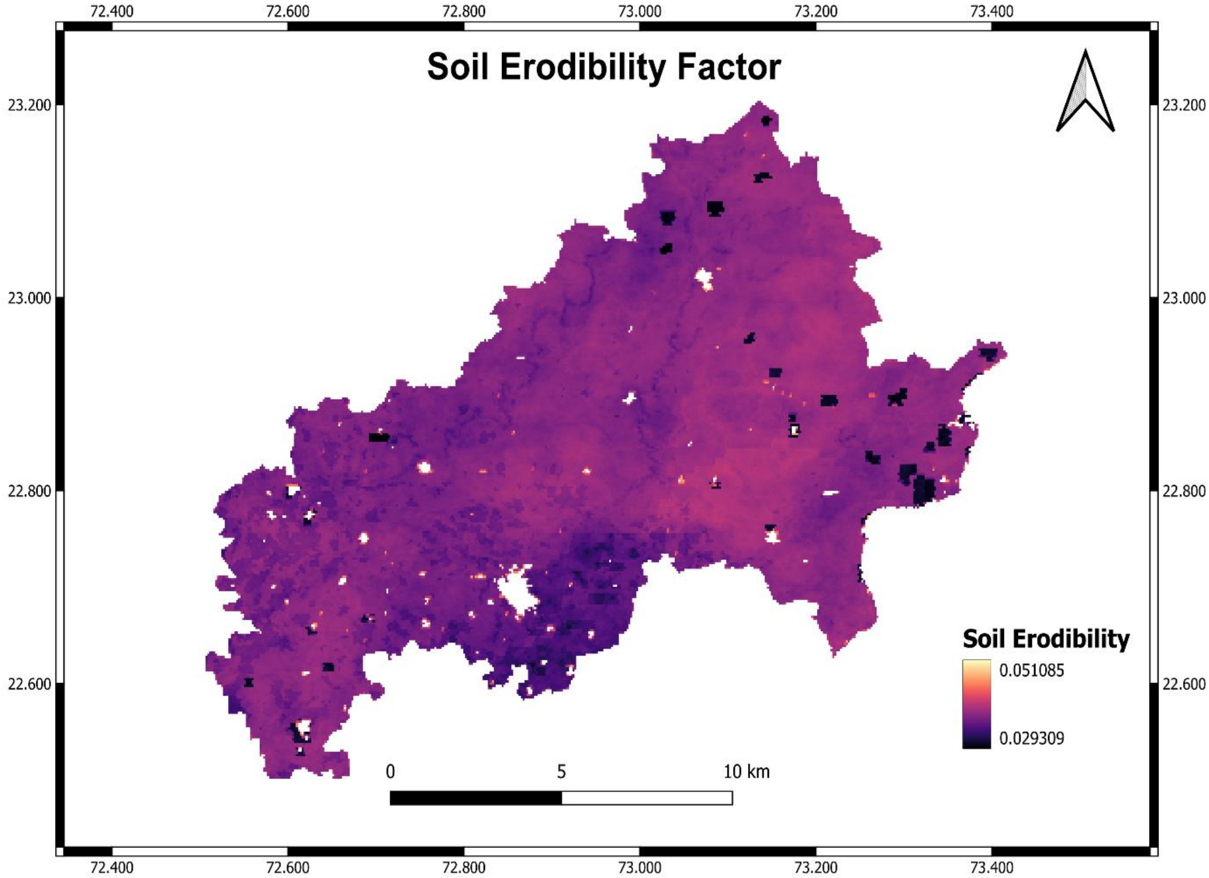

Fig. 11. Soil Erodibility Factor of the area.

5.3. Slope length and steepness factor (LS Factor)

LS factor ranged from 0 to 11.87 with a mean value of around 5.9, in the study area. The higher LS values may also be attributed to the abrupt slope variations near drainage channels and the highly dissected topography. Areas with longer and steeper slopes show higher LS factor values, indicating a greater potential for soil erosion due to the increased velocity and volume of runoff. The LS factor map highlights zones of varying erosion risk across the study area. In my study area, high LS factor values were observed near the Vatrak River, indicating an increased risk of soil erosion in these areas due to the steep and long slopes associated with the river's course.

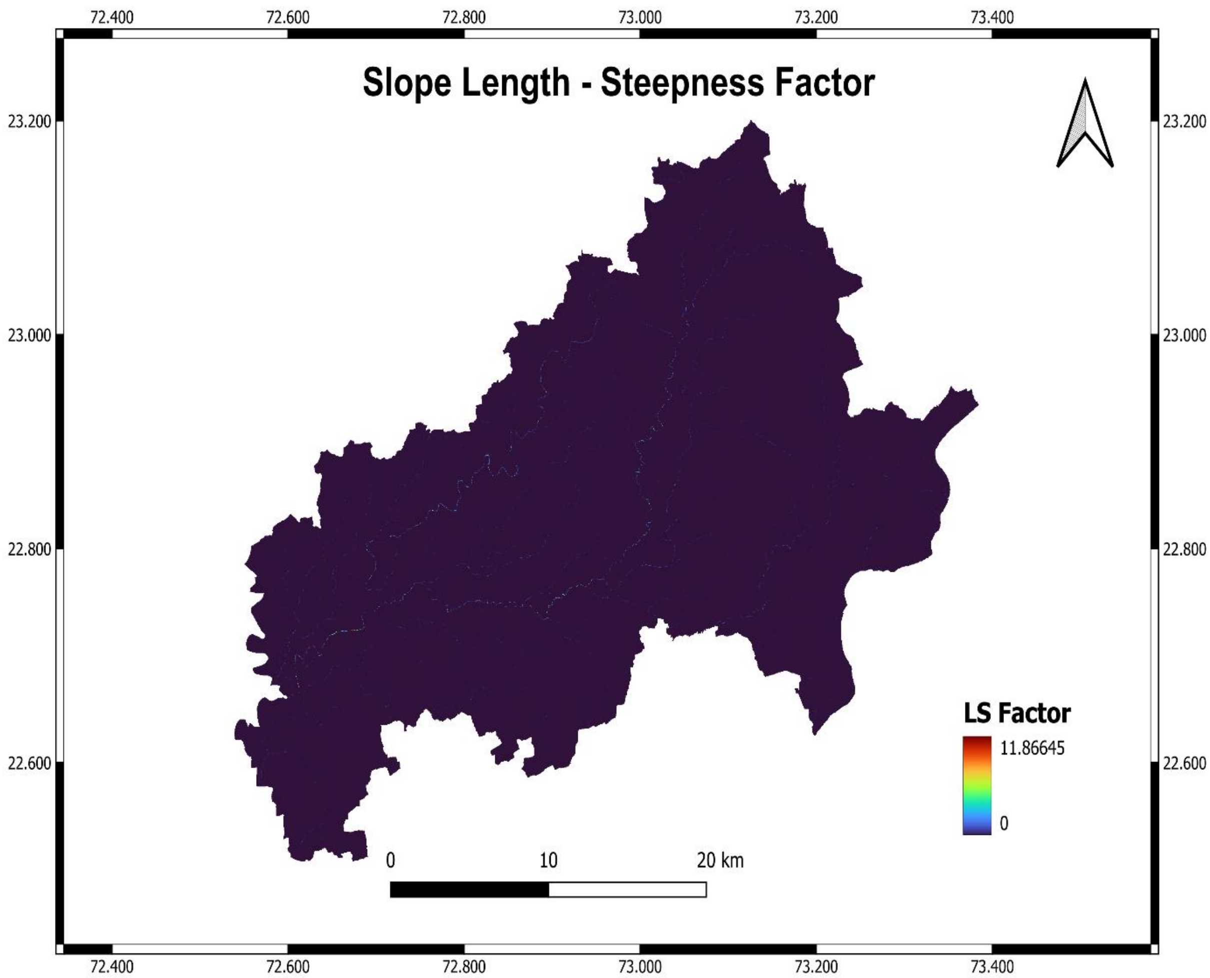

Fig. 12. Slope length steepness factor of area.

5.4. Crop cover and management factor (C Factor)

In the study area of Kheda district in Gujarat, the C factor values varied from 0.005 to 0.9 and mean value is around 0.45. The C factor values were assigned based on different aspects such as tillage practices, plant residue retention, and crop cover. The map illustrates the variations in C factor values, which range from low to high, depending on the type and extent of vegetation cover in each region. Areas with lower C factor values correspond to regions with dense vegetation cover, such as forests, which effectively protect soil from erosion. In contrast, areas with higher C factor values indicate regions with less vegetation cover, such as agricultural fields and wastelands, where soil erosion risk is higher due to reduced protection.

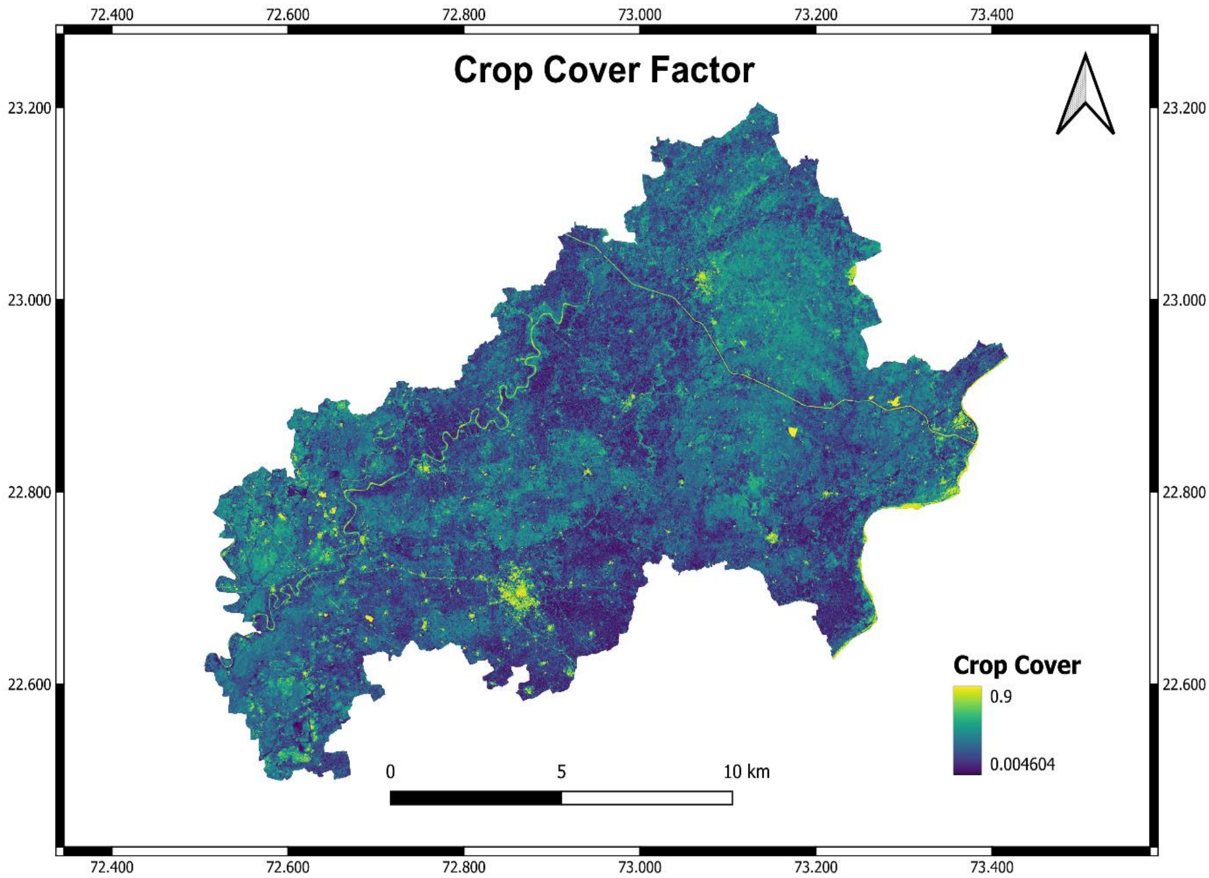

Fig. 13. Crop cover management factor.

5.5. Conservation practice factor (P factor)

P factor which represents the anthropogenic effects on soil erosion varied from 0 to 1. The highest values were assigned to LULC classes where no support practices are followed or adopted, lower values were assigned to built-up land, and different cropland classes, where different support practices such as bunding, terracing etc were adopted. The mean P factor value of the entire study area was found to be 0.56.

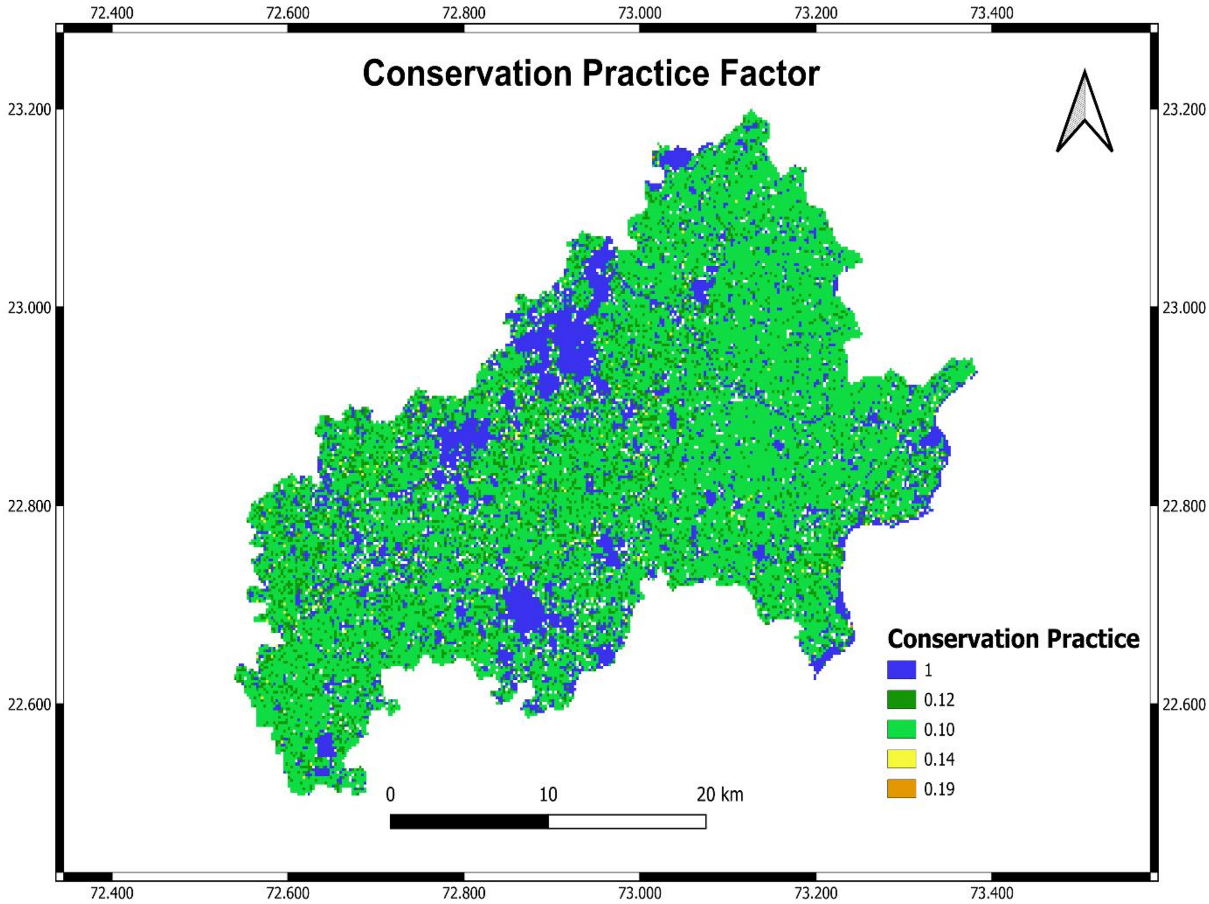

Fig. 14. Support practice factor map of the area.

5.6. Potential soil erosion rates

The soil erosion final map created using the RUSLE model of soil erosion provides a comprehensive view of soil erosion across the Kheda district. On average, the mean soil erosion in the district is around 1.5 tons per hectare per year. The map highlights significant variations across different regions within the district, reflecting diverse environmental factors and land use practices.

Certain areas in Kheda district exhibit higher soil erosion rates, such as Kheda taluka, with a mean erosion rate of 2.31 tons per hectare per year. These areas face challenges and may require immediate attention to address soil erosion and implement sustainable land management strategies. Conversely, regions like Thasra and Galteshwar talukas display lower erosion rates, indicating effective soil conservation practices and potentially more stable terrain. Other talukas fall in between these extremes, with moderate erosion rates such as in Kapadvanj, Kathlal, and Nadiad. These areas may benefit from proactive measures to prevent an increase in erosion and to maintain agricultural productivity and environmental health.

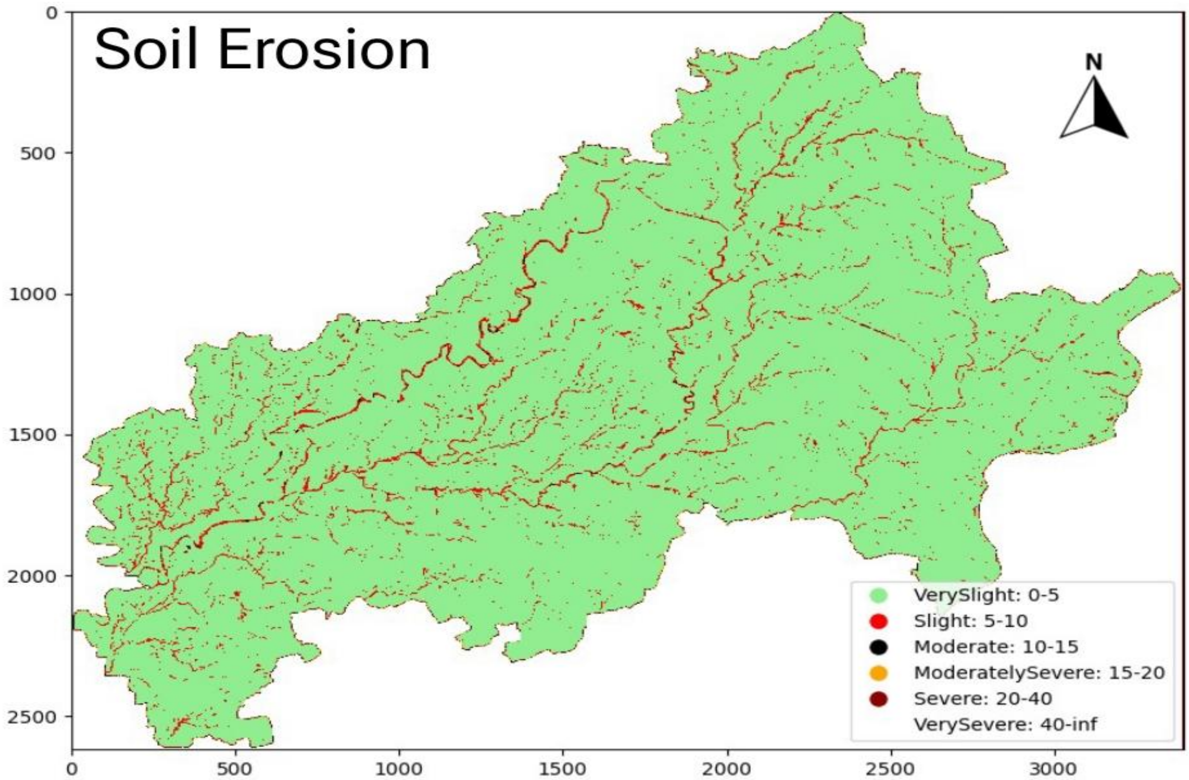

Fig. 15. Potential soil loss map of Kheda.

5.6.1. Soil erosion across various subdistricts

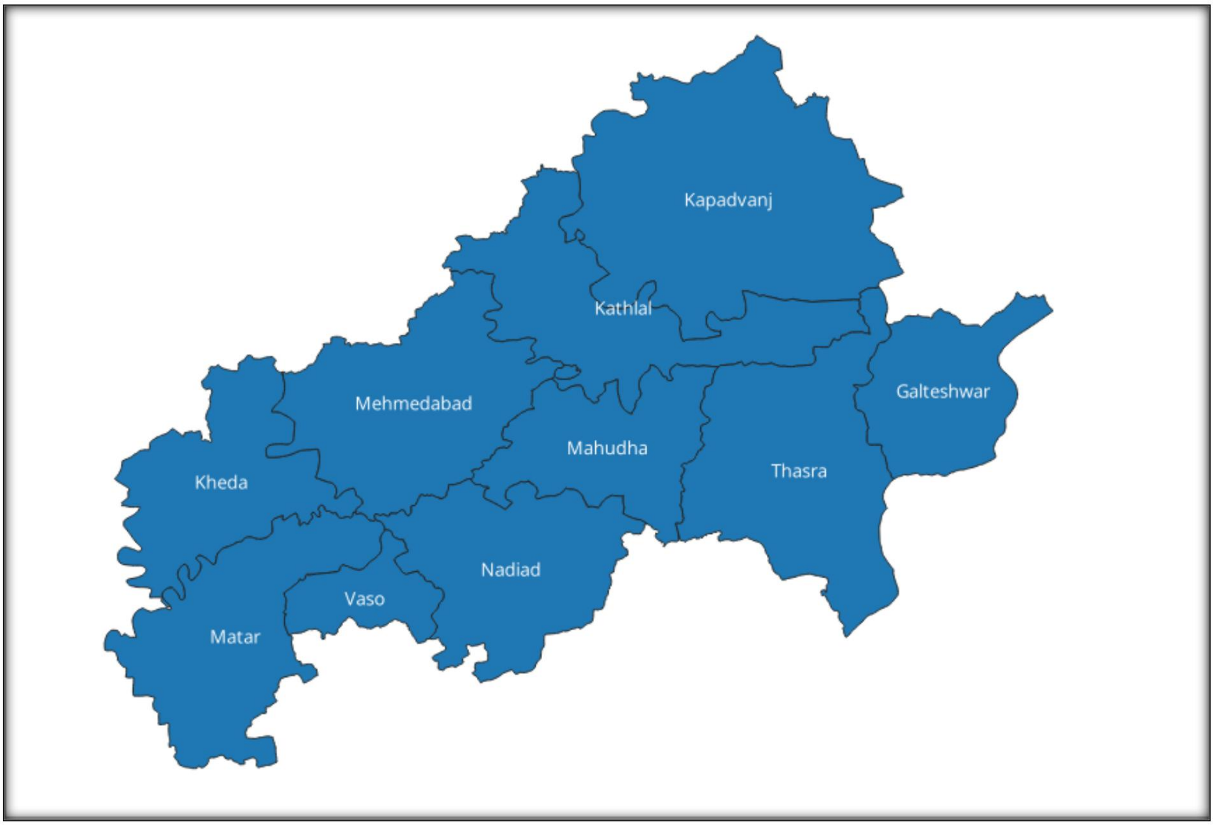

Fig. 16. Kheda Subdistricts.

Subdistrict	Mean
Galteshwar	0.99
Kapadvanj	1.13
Kathlal	1.39
Kheda	2.31
Mahudha	1.85
Matar	1.67
Mehmedabad	1.93
Nadiad	1.23
Thasra	0.84
Vaso	0.95

Table 2. Soil erosion across various subdistricts.

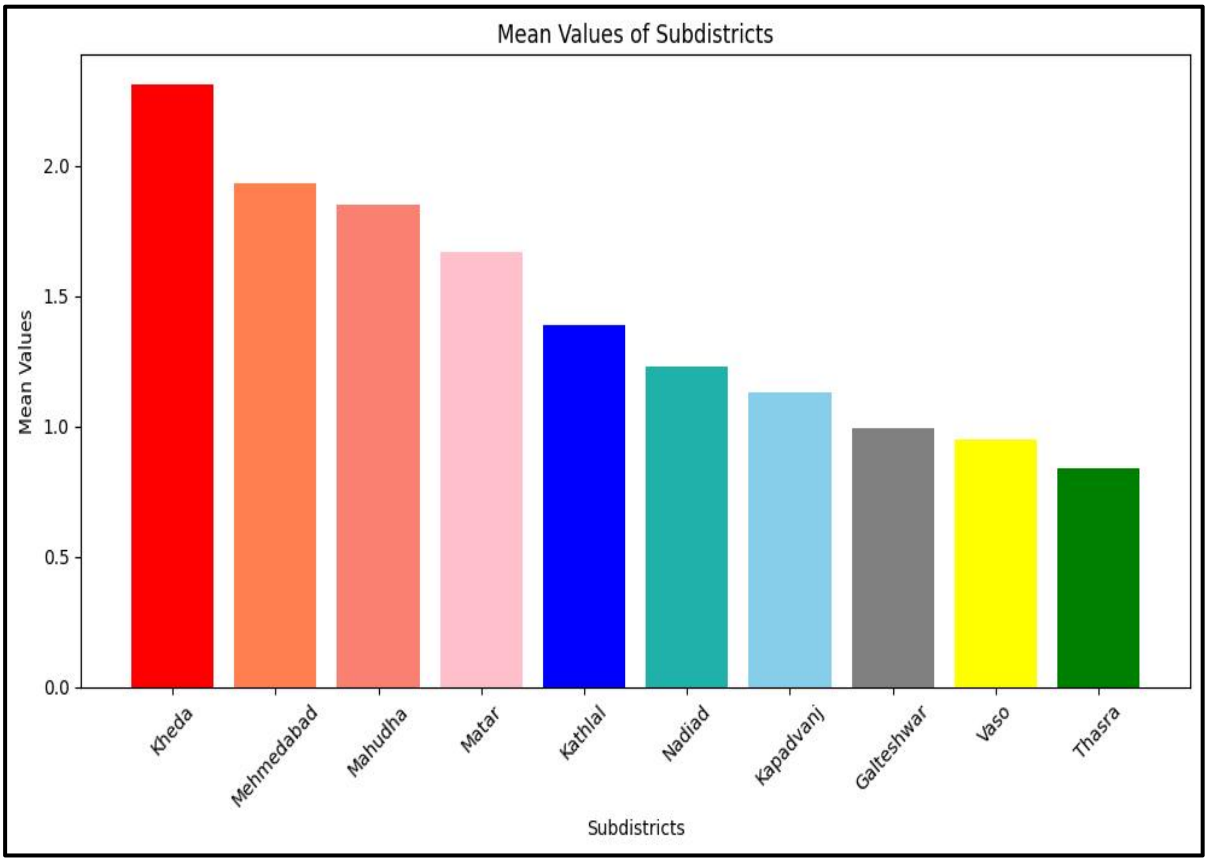

Fig. 17. Soil erosion across various subdistricts.

5.6.2. Soil erosion risk classes

The study area was classified into six erosion classes (Table 3).

Erosion class	Soil erosion rate (t ha−1 yr−1)
Very slight	0–5
Slight	5–10
Moderate	10–15
Moderately severe	15–20
Severe	20–40
Very severe	>40

Table 3. Soil erosion risk classes.

6. Conclusion

While Kheda district experiences moderate soil erosion on average, a closer look reveals a patchwork of vulnerability. Rainfall patterns play a role, with central and eastern areas receiving bursts of intense rain that can dislodge soil. The soil itself is naturally resistant to erosion thanks to vegetation and organic matter. However, the land's topography creates challenges. Steeper slopes are more prone to erosion, with rainwater washing away valuable topsoil. Vegetation cover acts as a shield, but areas with sparser plant life are more at risk. Finally, land management practices can tip the scales. Unsustainable practices can accelerate erosion, while conservation efforts can mitigate it.

The combined effect of these factors paints a nuanced picture. The average erosion rate of 1.5 tons per hectare per year masks significant local variations. About 75.26% of total geographic area of district having none to slight soil erosion, whereas about 11.68% suffers from slight to moderate & 8.33% area of district of suffers due to severe soil erosion.Some areas, like Kheda taluka, face a more severe threat due to a confluence of factors. Conversely, Thasra and Galteshwar talukas experience lower erosion rates. This spatial variability underscores the need for targeted solutions. Implementing soil conservation strategies in vulnerable areas is crucial. By addressing slope management, promoting vegetation cover, and encouraging sustainable land practices, we can safeguard Kheda district's agricultural productivity and ecological health for the future.

The soil erosion final map serves as an essential tool for guiding conservation efforts across the district. By focusing on regions with higher erosion rates and supporting the continued success of areas with lower erosion rates, stakeholders can work towards a sustainable and productive agricultural future in Kheda district.

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