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APPLICATION OF RUSLE MODEL FOR SOIL EROSION ESTINATION: A STUDY OF TULSI RIVER WATERSHED, MAHARASHTRA, INDIA

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ABSTRACT

Fertile agriculture land is most valuable resource on the earth which is declining very rapidly. Soil erosion is predominantly anthropogenic and is a serious environmental concern due to land use conversion, agricultural intensification, and other human activities. Soil erosion brings about a significant threat to agricultural productivity, water quality, and ecosystem stability. To effectively monitor and mitigate soil degradation, it is crucial to evaluate soil loss accurately and efficiently across diverse landscapes. Using satellite remote sensing and Geographic Information Systems (GIS), spatial data layers corresponding to the five RUSLE factor Rainfall erosivity (R), Soil erodibility (K), Slope length and steepness (LS), Cover management (C), and Support practice (P) are generated and analyzed. This concept proposes the integration of geospatial techniques with the Revised Universal Soil Loss Equation (RUSLE) model for the estimation and spatial assessment of erosion vulnerability. Erosion estimations aid in basin or watershed planning and conservation. This impoverishment reduces the ability of seeded stream to infiltrate, while with the decrease in fertility, a seeded stream can elevate. Therefore, it is hardly surprising that production is affected. The present work aims at estimating the annual soil loss in the Tulsi watershed, Maharashtra using the model RUSLE, based on RS and GIS. The investigation uses the RUSLE model that involves five essential input parameters: rainfall erosivity factor (R), slope length and steepness factor (LS), soil erodability factor (K), cover management factor (C) and conservation practice factor (P). Three erosion risk categories were the following: Slight (0-1 tonha/year) Moderate (1-5 ton/ha/year) and Sever (> 5 ton/ha/year). Most of the research area (74 sq. km.) was found to be severely degraded. A better approach to evaluate depletion of soil in this study was "RUSLE", as found in the analysis. Soil conservation and management should address centers which possess the greatest rates of soil erosion suggested by the data.

Keywords: - Soil erosion model, LULC, RUSLE, Watershed, Erosion control & management practices.

1. INTRODUCTION

Soil and water is essential a ecological resource has needed to be conserve for environmental and social wellbeing (Panhalkar & Mali, 2021; Wassie, 2020). Soil erosion remains one of the most critical forms of land degradation, posing a severe hazard to agricultural productivity, environmental sustainability, and socio-economic progress. Soil erosion caused by runoff is a very serious and threatening geo-temporal problem throughout the world (Khan et

10.48047/jocaaa.2024.33.02.30

al.,2022). That's a process of sweeping up soil, moving it elsewhere and redepositing the particles there. Soil erosion, being a "soil cancer" due to its widely-felt social and environmental consequences, both seen and unseen. Some 53% of the country is at risk for at least one form of erosion and each year, due to various reasons, as much as 5,334 MT of soil is lost (Narayana & Babu, 1983). The problems are manifold due to soil erosion, the most important of which are reduction in aesthetic landscape beauty, increased likelihood of floods in flood plains, decreased quality of water, and put land under fallow land. Such land it is not suitable for reforestation because of the reduction in fertility and productivity.

India is an agrarian country and around 60% Peoples reliant on agriculture. According to Desertification and land degradation atlas published by ISRO SAC, approximately 29% of land area degradation during 2018-19. Maharashtra is one of India's leading agrarian states, with a substantial portion of its population dependent on agriculture for livelihood (Raman and Khan, 2020). However, the state faces several challenges related to soil erosion, land degradation, and declining soil fertility due to numerous factors. about 1.4 million hectares are affected by desertification, and 16.7% of India's total degraded land is located in Maharashtra. Many farmers of Maharashtra face failures in farming due to intensive erosion (Joshi, Susware, & Sinha, 2016).

On a catchment basis, in which the evaluation of soil erosion requires the management of large spatial data sets and large-basin size, the application of remote sensing and Geographic Information System (GIS) has demonstrated to be a powerful and convenient tool for monitoring, analysing and estimation of soil erosion through its precise mapping (Senanayake et al., 2020). Satellite-based remote sensing images of the Earth's surface provides current land use and land cover data that can be efficiently retrieved to help one find areas vulnerable to erosion and its effective planning. RUSLE (Revised Universal Soil Loss Equation, by Renard et al., 1991), FUSLE (Universal Soil Loss Equation for Forests, Jin-Chi et al, 2008).

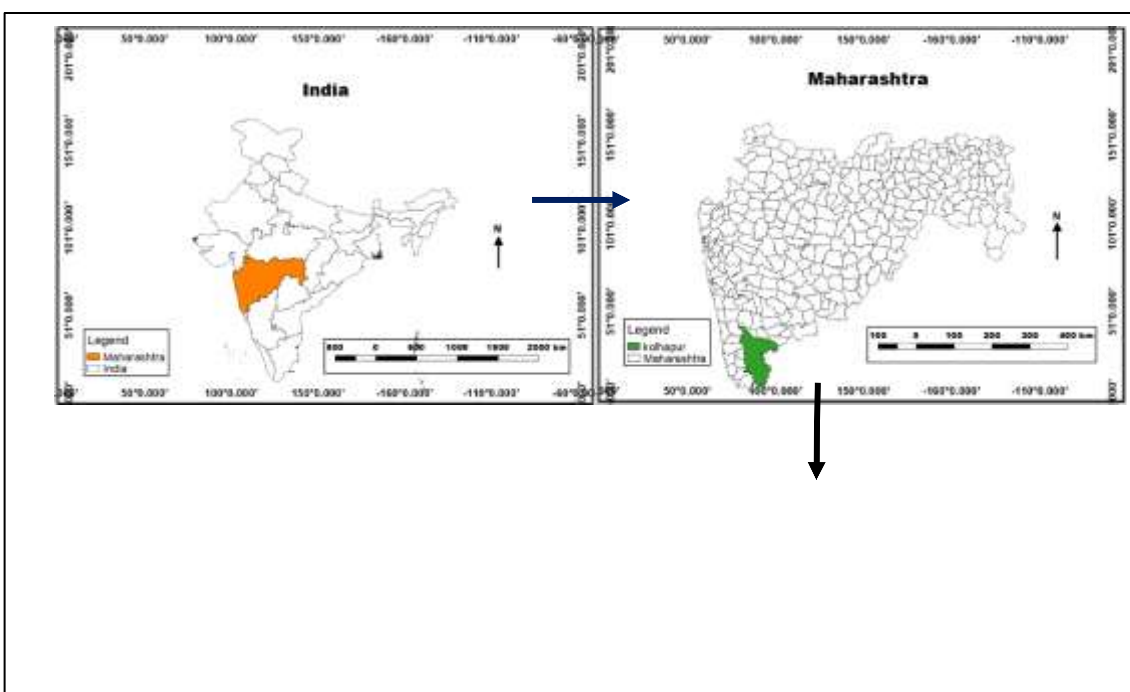
In addition to the widely used soil erosion assessment models, several other models have been developed and applied for specific purposes and conditions (Borrelli et al., 2020). These include the EGEM developed by the USDA-SCS (1992), the ANSWERS by Beasley et al. (1980), and the SWAT by Arnold et al. (1993). The WEPP, initiated by USDA-ARS in 1995, is another significant advancement. Furthermore, the WaTEM by Van Oost et al. (2000), the SEDEM by Van Rompaey et al. (2001), and the USPED model by Mitasova et al. (1996) have all contributed to erosion assessment. Additionally, the AGNPS developed by Young et al. (1989) has been instrumental in evaluating water quality impacts from agricultural runoff. To determine the extent of soil erosion in settings other than pilot sites, like forests or pastures, the RUSLE model was created in 1996. A number of new variables were announced for RUSLE, including an updated weather factor, a revised method for calculating the over vegetation factor, and updated length and gradient of slope calculations (Ghosal and Das, 2020). The improved RUSLE model can be applied to evaluate soil erosion at the micro, meso and macro levels. The Tulsi River is one of the principal rivers in Kolhapur district with a large catchment and population. The erosive capacity is high and impacts the landscape. It is essential to study soil erosion and recommend preservation in the study region

10.48047/jocaaa.2024.33.02.30

to counteract it. The Tulsi River watershed region is selected using the RUSLE model, which is acknowledged and used worldwide for predicting of soil erosion. The objective of this study is to compute the RUSLE parameters using GIS techniques and to estimate the annual average of soil loss due to erosion across the entire Tulsi River watershed.

2. STUDY AREA

The Tulasi Catchment is one of the sub-watersheds of the Bhogawati River watersheds in the Kolhapur district, Maharashtra, India (Pawar-Patil et al., 2023). The Tulsi River is a river flowing southwest to the northeast between Radhanagari and Karveer tahsils of Kolhapur and it has an approximate area of 163 km². The watershed is located between 16°27′N to 16°39′N latitude and 73°57′E to 74°08′E longitude. Elevation in the watershed differs between 543 to 994 metres above MSL. The southwestern part of the basin is covered by spurs of Western Ghats and it has undulating rocky terrain, whereas the northeastern half is mostly flat with fertile alluvial soil. The region has a monsoon type of climate and there is an appreciable spatial variation in the rainfall the maxima being on the southwest (due to the orographic effects) decreasing towards the east.



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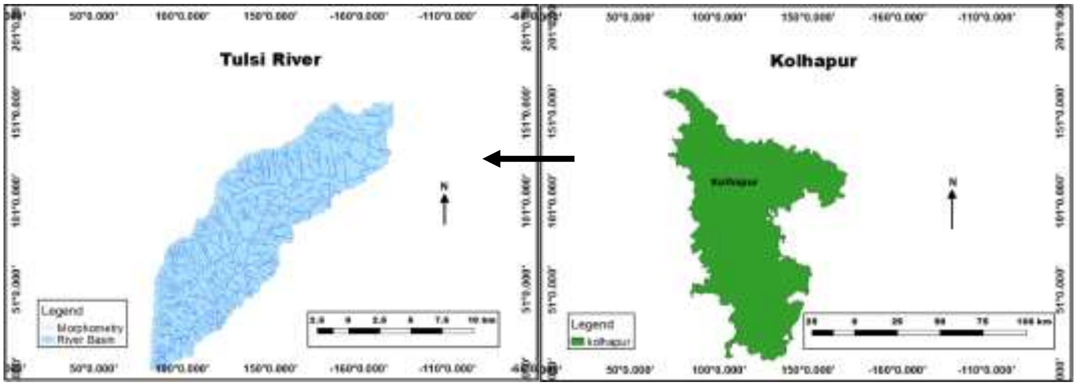

Figure 1: Location Map of study region

3. DATA BASE AND METHODOLOGY

Conventional approaches to estimate the degree of risk of erosion in soils are typically time-consuming, cost-inefficient and not effective for large spatial scales (Liu et al., 2023). To overcome these limitations, the combination of field measurements with existing soil erosion models and remotely sensed products have been developed and proved to be a powerful technique via GIS (Fernandez et al., 2003; Gitas et al., 2009; Xu et al., 2009). One important type of geospatial data for soil erosion modeling is DEM, which is necessary for topography-based modeling and can be acquired by optical or SAR (microwave) stereo sensing (Kim, 2006).

The model RUSLE is commonly used for the estimation of the long-term yearly average soil loss due to rainwater and surface runoff (Thapa, 2020). The RUSLE model is employed in a GIS environment in this study at raster level (pixel-by-pixel basis), and the spatial prediction of soil erosion potential within the Tulasi watershed is realized. This pixel-wise approach improves the capacity to identify and display spatial variability in erosion risk in heterogeneous natural landscapes (Shinde et al., 2010).

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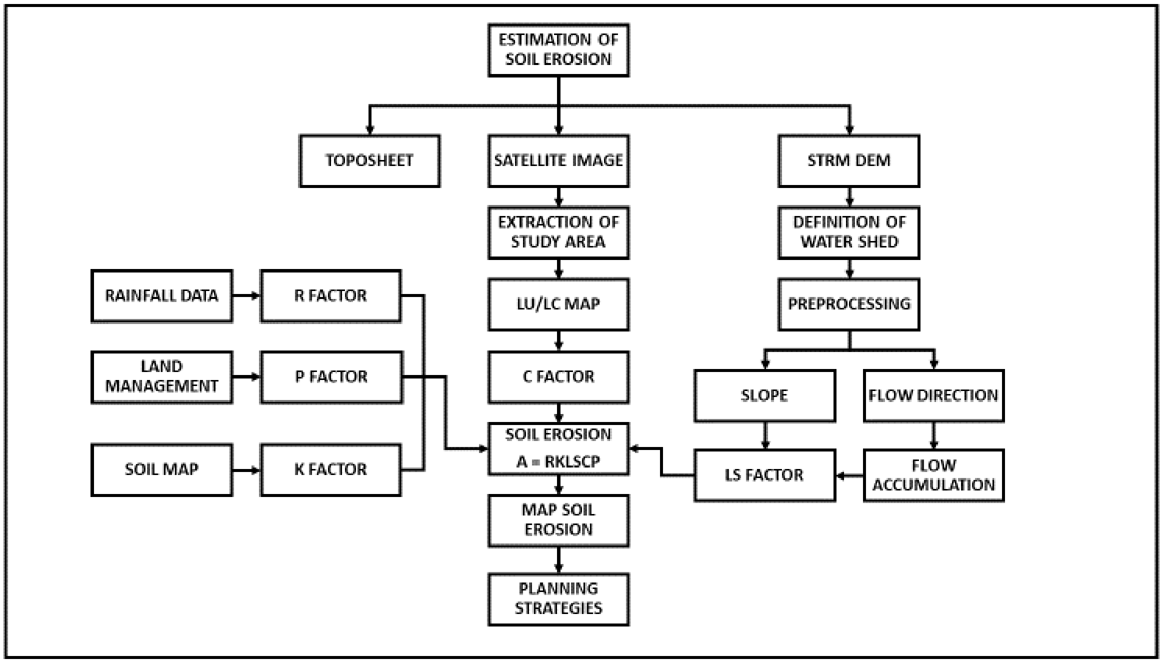

Figure 2: Flow chart depicting methodology of RUSLE Model.

All RUSLE parameters were based on relevant satellite datasets, slope, climatic data, field measurements and empirical formula applicable to the Indian monsoon terrain. Each factor were calculate the final soil erosion output.The methodology adopted in this study is illustrated in Figure 2. It begins with data acquisition, including DEM, soil data, land use/land cover and precipitation data. Each RUSLE factor is then calculated and incorporated within a GIS framework to generate a composite geospatial soil erosion risk map. Furthermore, an overlay analysis was employed to delineate soil erosion susceptibility zones, enabling the identification of critical hotspots for prioritizing soil conservation measures.

4. Results and Discussion

4.1 SOIL EROSION ESTIMATION OF TULASI RIVER

Soil erosion imposes great threats to soil health, agricultural production, water quality, hydrological functions, and overall ecosystem functioning, which are reflected in long term human sustainability (Borrelli et al., 2020). Quantifying soil erosion losses, however r, still remains a daunting task because several drivers such as climate fluctuations, land cover dynamics, soil properties, topography and human interferences, interact directly or indirectly with soil erosion patterns (Mbugua, 2009). When we get into the specifics of the modelling part of predicting the risk from soil erosions, particularly in updating to the spatial in designing what erosion control measures we should establish in the landscape, the spatial risk has become increasingly important to land managers, planners, and policy makers, who are looking for something more operative than the larger erosion loss values. In that sense, the coupling of soil

10.48047/jocaaa.2024.33.02.30

erosion models and GIS has been established as a popular and effective method for assessing and mapping soil erosion at different scales (Abdelsamie et al., 2022). Different erosion simulation models have been established during the past decades, including PSIAC, WEPP, EPM, and MMF model, which have contributed to the literature providing supportable tools to forecast soil erosion in a watershed. USLE is one of the commonly used empirical models worldwide among these. Developed by Wischmeier and Smith (1978) for the USDA in the 1950s, the USLE estimates annual soil loss from sheet and rill erosion in croplands. Later improvements resulted in the development of MUSLE in 1970s to add the role of flow energy to event-based predictions. The latest modification, RUSLE (Millward and Mersey 1999), substituted the runoff factor with a more robust factor (rainfall erosivity) and improved the model's applicability to various climatic and physiographic conditions. RUSLE has now been accepted generally as a technique for the spatial geostatistical analysis of soil erosion when combined with remote sensing and GIS facilities.

The RUSLE model was applied in this research because it has been commonly employed and successfully applied for soil erosion prediction in various regions and under different environmental conditions. RUSLE, in comparison to that of the original USLE (Wischmeier & Smith, 1978), provides greater accuracy from methodological advances and revised parameter values (Renard et al., 1997). RUSLE is also very flexible and can be adapted to fit varying land use and location-specific conditions thus, it serves as a good model for prediction of soil erosion in modifying environmental situations. Besides, its easy embedment in Geographic Information System (GIS) enables spatial explicit analysis of soil erosion risk, which could be useful for the development of integrated watershed management or conservation plan (Wischmeier & Smith, 1965).

The RUSLE model can be expressed as Equation:

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

Where,

A = Average annual soil loss per unit area per year (t/ha per year)

R = Rainfall Erosivity Factor (MJ mm ha-1 h^{-1} $year^{-1}$)

K = Soil Erosivity Factor (t ha MJ^{-1} mm^{-1})

LS = Slope Length and Steepness Factor

C = Cover and Management Factor

P = Conversation Support Practice Factor

4.1. RAINFALL EROSIVITY FACTOR (R)

10.48047/jocaaa.2024.33.02.30

The Rainfall Erosivity Factor (R) indicates the effect of rainfall intensity and amount on soil erosion, serving as a critical input in the RUSLE model (Wischmeier & Smith, 1978). This variable effectively measures rainfall erosivity by combining the two main characteristics of a storm: the total amount of rain, and the intensity peak. Kinetic energy of raindrops and the resulting water runoff exert strong effects on removal and transport of soil particles from the tilled fields (Zhang, 2023). Therefore, the R-factor needs to be an effective representation of both raindrop impact energy and the runoff-producing potential of the precipitation events. In practice, the R factor is often calculated from measured rainfall intensities, where they are available. In places with few intensity observations, empirical equations based upon local conditions are typically employed instead. In the current analysis, monthly rainfall data of 5 rain gauges within the Tulsi River Basin (2011-2024) from the Hydrological Data User Group (HDUG), Water Resources Department were gathered. To assess the spatial variation of the R-factor and to construct a map of rainfall erosivity, the study utilized the empirical equation proposed by R. Babu and others. (2004), specifically quoted for Indian conditions and often used in related hydrological and soil erosion studies.

Annual Relationship:

$$\mathbf{R = 79 + 0.363R_N} \qquad (2)$$

Where,

R_N is the average annual rainfall in mm.

Average annual R factor values have been estimated depending on the rainfall for the period 2011-24. The rainfall data is used to obtain a typical rainfall distribution map. The most suitable interpolation method used is Inverse Distance Weighted (IDW) because this method presented an almost true behaviour of the rainfall distribution map (Wuthiwongyothin et al., 2021) (Figure 3), which is used as input in R-factor estimation.

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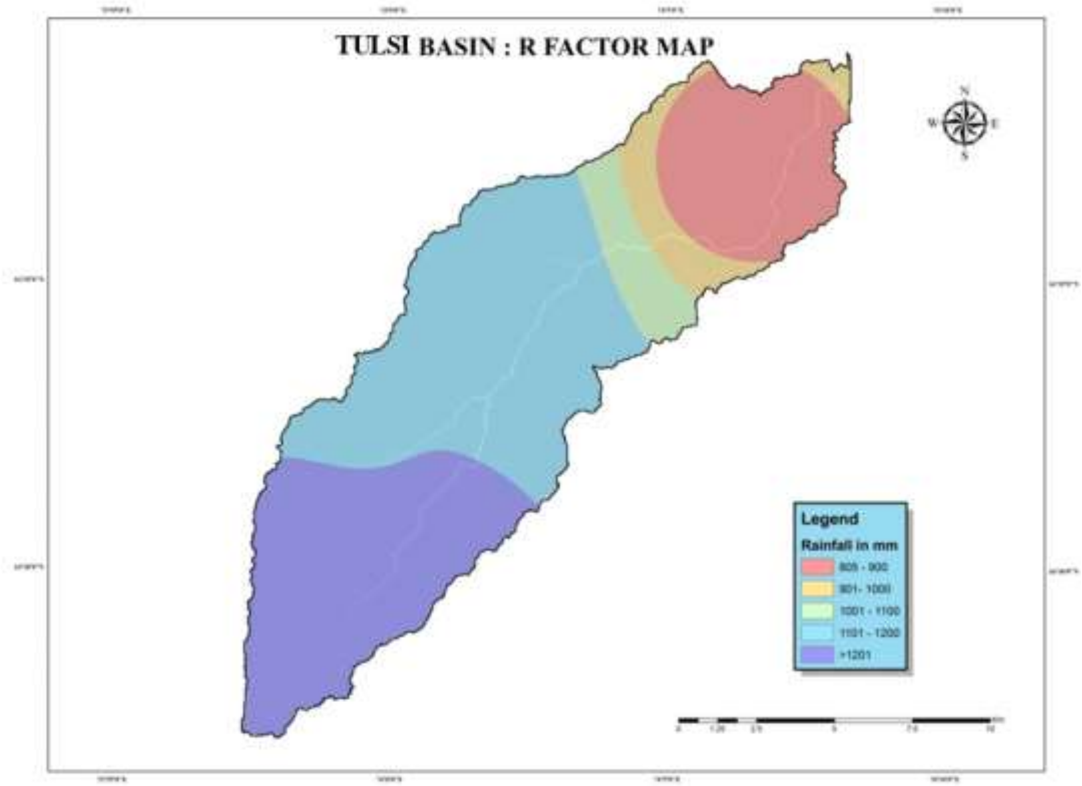

Figure 3: Rainfall Erosivity Factor (R).

The rainfall erosivity (R) factor was developed using Inverse Distance Weighted (IDW) technique throughout the Tulasi watershed. The computed values of R, which are a measure of (the annually averaged) rainfall erosivity, varied between 800 and 1276 MJ mm ha^{-1} h^{-1} yr^{-1}. From this data, a spatially distributed rainfall and runoff erosivity factor map (Figure 3) was created in ArcGIS. This map was obtained from the annual distribution of rainfall, and the R factor values (2000 to 3300 ha·mm/hr·yr) were combined by using empirical equations. The result is a comprehensive depiction of erosive potential influenced by rainfall intensity and distribution over the watershed.

4.2 SOIL ERODIBILITY FACTOR (K)

The K factor is a function of a number of soil properties including particle size distribution, soil structure, soil organic content and its permeability that contribute to soil erodibility (Ostovari et al., 2022). Together these properties determine how vulnerable soil is to erosion and how resistant it is to the forces of water and wind. According to Wischmeier, Johnson, Cross, and coauthors (1971), the knowledge of these input soil characteristics is fundamental for the precise prediction of the danger of erosion and the achievement of proper soil conservation measures. The K factor of soil erodibility ranges from 0.02 to 0.69. Due to the low K value for the high clay, of 0.05 – 0.15, and low value of the coarse texture sand (0.05-0.2), which does not exceed the difference is mainly caused by the soil's detachment resistance. The most significant

10.48047/jocaaa.2024.33.02.30

factor of erodibility of soil is the top soil type. The silt % content in regards to the whole topsoil is due to fact that it can easily detach and crusting so high of runoff. Well, the soil is with elevated silt content and it's the most erodible of all soil type. The organic carbon level is a calculable factor for soil erosion. Soil erodibility factor in this study was computed based on its content of silt, very fine sand (0.002–0.1 mm), sand (0.1–0.2 mm), and soil organic matter. To ensure realistic spatial distribution, the soil information was sourced from the Digital Soil Map of the World (DSMW) of the UN-FAO, 2007. Such a comprehensive dataset formed a reliable platform for assessing soil erodibility in the study region The DSMW and IPAW offer information such as environmental, chemical and biological properties of the soil. One commonly applied relation we have also used a rather influenced relationship for erodibility, proposed by Wischmeier & Smith (1978). The analytical expression is corresponding to the regression equation:

$$\boldsymbol{K} = \frac{[2.1x10-4(12-OM)M1.14+3.25(s-2)+2.5(p-3)}{759.4} \quad (3)$$

Where,

OM is Organic Matter, s is structural code, p is permeability code and M is calculated as follows: M = (%very fine sand) x (100 - %clay**),** M is the particle size parameter. K values in (tones MJ-1 hmm-1) were calculated using the regional soil map and the aforementioned formulae were utilized to construct a K factor map.

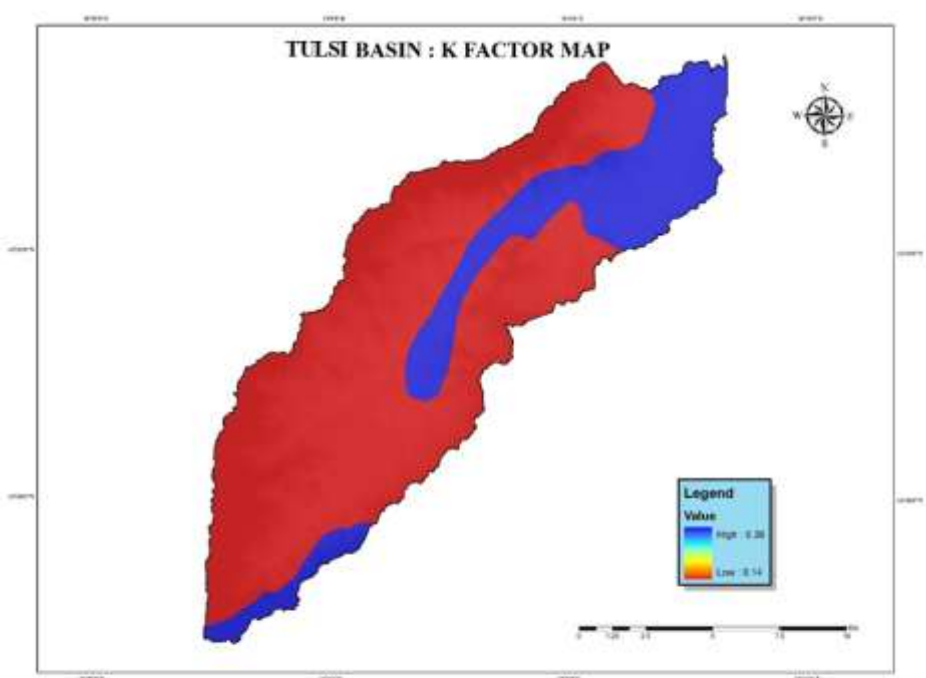

Figure 4: Soil Erodibility Map (K).

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The RUSLE, K is considered constant over the year. Table of K value are calculating with the help of soil and crop management studies NBSS & LUP, Nagpur. It measures with the help of soil structure, organic content and soil permeability values. Soil erodibility is predicted as a function of soil properties and profile characteristics.

- ✓ Percent silt (MS; 0.002-0.05mm).
- ✓ Percent very fine sand (VFS; 0.05-0.1mm).
- ✓ Percent sand (SA; 0.1-2mm)
- ✓ Percent organic (OM).
- ✓ Structure code (s).
- ✓ Permeability code(p).
- ✓

Soil erosion can be quantified with the use of this factor, which indicates the soil's aptitude or vulnerability to erosion. This component is conditional on the soil type and texture. The K factor was determined using Equations 3.

4.3. SLOPE LENGTH AND SLOPE STEEPNESS FACTOR (LS)

The RUSLE model takes into consideration the L-S factor, which is the most important topographic variable influencing soil erosion vulnerability (Datta & Schack-Kirchner, 2010; Prasannakumar et al., 2012). Topographic factor (LS) reflects the topographical influence in sheet and rill erosion. Field measurement or a DEM can help one estimate the two. They have to be examined jointly since the angle and the length of slope affect the magnitude of erosion. Though there are several relationships for estimating LS factor, the one most appropriate for integration with GIS suggested by Wischmeier (1978) using unit stream power theory has been employed; the equation is as follows:

$$LS = \left(\frac{L}{22.13}\right) mX(0.65 + 0.45.S + 0.065.S^2) \qquad (4)$$

Where,

A is unslope contributing factor B is the slope angle.

L= slope length (meters)

S = angle of slope (persent)

m = constant dependent on the value of the slope gradient.

S = Slope of DEM

A higher-resolution digital elevation model (DEM) will allow for more accurate estimations. Based on the flow accumulation and slope steepness, the LS map was generated using a raster calculator according to Bizwuek et al. (2008).

The expression used as follow

10.48047/jocaaa.2024.33.02.30

$$LS = Pow\left(FA\frac{CS}{22.13}\right)0.4X(0.65 + 0.45.S + 0.065.S^2) \quad (5)$$

Where,

FA = flow accumulation

CS = grid size

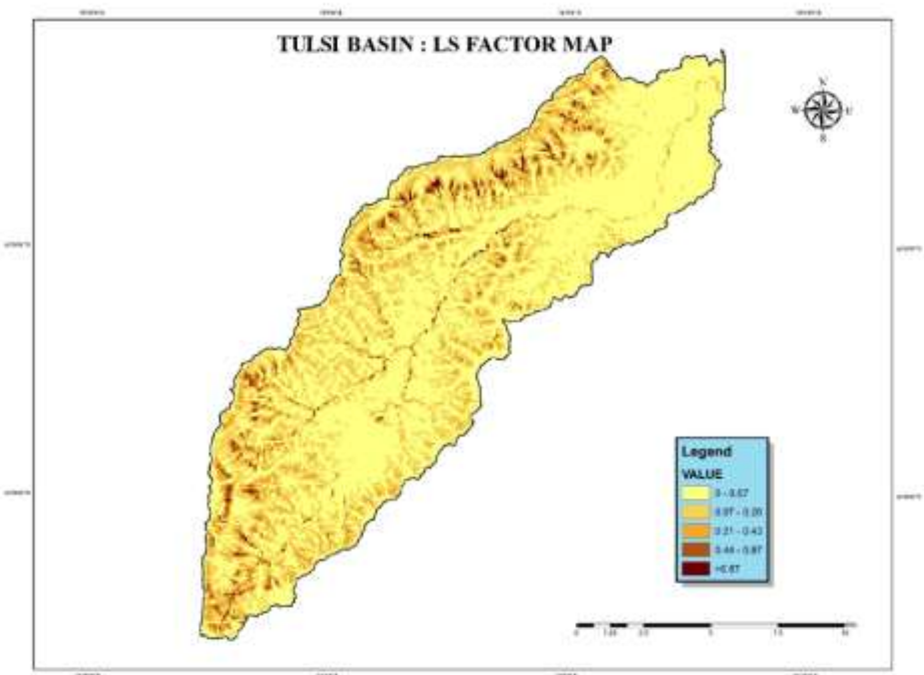

Figure 5: Slope Length and Slope Steepness Map (LS).

This slope value was obtained using the Tulasi River watershed SRTM, Digital Elevation Model (DEM). DEM provided us with the X and S values. The Arc Hydro tool in ArcGIS environment was used to extract the Flow Accumulation from the DEM after the Fill and Flow Direction processes. The slope length (X) value was then computed. Most of the area falls between 13 and 20% for this value (0–2.44). High appraisals left little room for forest land, lowlands, and hills.

4.3. COVER AND MANAGEMENT FACTOR (C)

The cover management factor (C) is expresses as the ratio of the soil loss from an area with specific vegetation and crop cover to that from a bare, continuously cultivated land that has the identical soil and slope characteristics (Pandey et al., 2007, Xiong et al., 2023). It is an important indicator in evaluating the impacts with respect to vegetation cover and land use on erodibility. The C factor, closely related to the percent of surface area covered by plants, is a measure of the impact of human activities, including plowing, grazing, and clearing, on soil stability. It includes elements of cover and land management, featuring the significance of vegetation for soil erosion control.

10.48047/jocaaa.2024.33.02.30

The land use and land cover classification was performed using satellite images obtained from the USGS Earth Explorer-landsat 9 in 2024 with a spatial resolution of 30 meters. The area of the basin was determined from satellite images by utilizing the "Raster Calculator" feature within the "Spatial Analyst" extension of the "ArcGIS" software suite. A number of studies have shown a correlation between NDVI values and C factor through regression analysis, which is used in erosion assessment to estimate C-factor values for different land cover categories. The NDVI, or Normalised Difference Vegetation Index, is the gold standard for measuring vegetation growth derived from remote sensing.

$$NDVI = IR\text{-}R \;/\; IR+R \qquad (6)$$

Where,
IR is the band 3 for near Infra-Red
R is the band 2 for Red region of visible spectrum

Using the aforementioned indication NDVI map was generate in the "ArcGIS" software which will be a basis map required for the manufacturing C factor map. In a doctoral dissertation, De Jong (1994) detailed the application of plant indices to draw plant characteristics for erosion models. The results of this study support the following: (i) a relationship between NDVI and C-factor (RUSLE), which is (ii) linear. Under the assumptions of the aforementioned regression analysis of the spatial distribution of NDVI value, a regression equation can be formulated for estimating the C-value. It is also important to exclude NDVI values below zero (normally indicating water or snow) from the regression analysis, since it does not contribute directly to the estimation of vegetation cover (Zhang et al., 2021). Consequently, the C-factor can be predicted based on the linear regression generated using NDVI data as described by the following equations.

$$C = exp\left[\propto \frac{NDVI}{(\beta - NDVI)}\right] \qquad (7)$$

Where,
α and β are the dimension less coefficients deciding the curvature in the curve of NDVI and that of C factor. Van et al. it is observed that applying this scaling was more efficient than assuming the relationship, and we chose 2 and 1 for the parameter α and β, respectively. Many of the researchers (Kouli et al. 2009; prannakumar et al. 2012). The C-factor was estimated using a NDVI map (a ratio of spectral values of near infrared and red reflectance) generated from the satellite imagery and 30 x 30 m resolution raster map was developed for the Tulsi River watershed, results are reported in figure 6.

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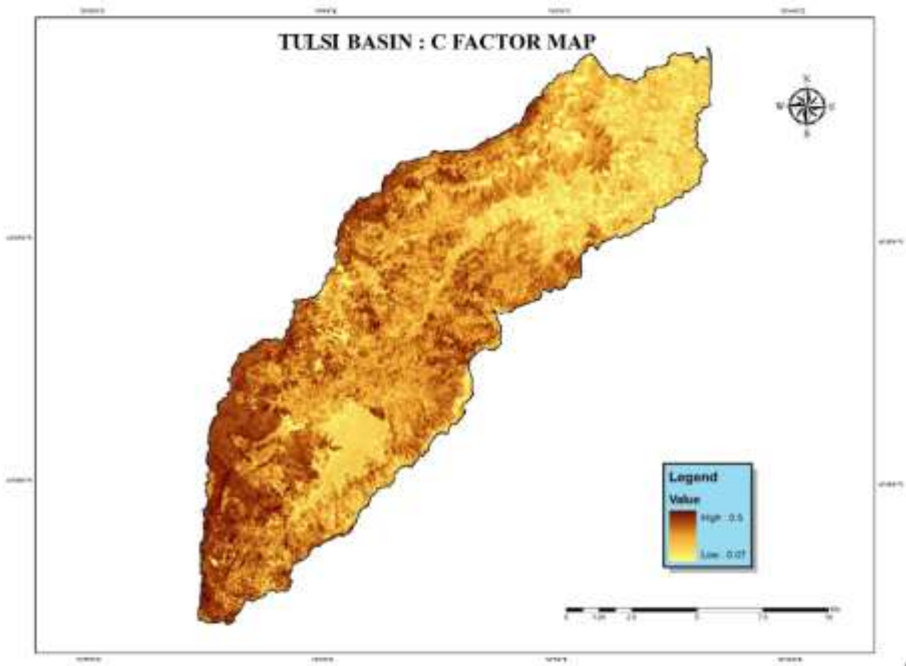

Figure 6: Cover and Management Map (C)

The cover management factor is defined as the ratio of soil loss from an area under a certain vegetative cover and management practice to the loss from a similarly eroded area under continuous tillage and bare fallow with the same soil type and slope (Prasuhn, 2022). It is a key factor in assessing the capacity for different land use and crop management options to reduce soil erosion. C factor in the current study was developed based on NDVI data from LISS-IV satellite image. C-factor values varied between 0.07 and 0.5, as observed in the NDVI analysis corresponding to different levels of vegetation cover and their contribution to erosion control.

4.4. CONVERSATION SUPPORT PRACTICE FACTOR (P)

The practice factor (P) is the ratio of soil loss with a particular conservation system to the corresponding loss under conventional up and down slope tillage (Wischmeier, Smith, 1978). This effect represents the presence of management practices (e.g. contouring, terracing, strip cropping) which change the direction and the flow pattern of the runoff, consequently reducing its speed and the erosive potential (Renard & Foster, 1983, Renard et al., 1997). In the present study, the P factor was derived by using remote sensing imagery in connection with LULC classification. As in Millyard and Mersey (1999) and Reusing (2000), it was hypothesized that the P factor value is similar for similar land cover types. An LULC classification map, which was generated based on LISS-IV Satellite data at 5.8 m spatial resolution, was used as the primary input data set for estimating P factor values for the Tulasi Watershed. The P factor varies from 0 to 1, with 0 meaning very effective human-implemented erosion prevention measures, and 1 meaning no such practices are us ed. These slope-based P values employed in this analysis are provided in Table 1.

10.48047/jocaaa.2024.33.02.30

Table 1: P- Factor Values for Different Land Use/ Land Cover

Sr. No.	Class Name	P Factor
1	River	0.003
2	Fallow Land	0.5
3	Water Body	0.003
4	Urban & Built Up	0.0
5	Barren Land	0.18
6	Open Scrub Forest	0.18
7	Dense Scrub Forest	0.0003
8	Scrub with Barren Land	0.18
9	Open Mixed Forest	0.18
10	Crop Land	0.5
11	Plantation	0.5

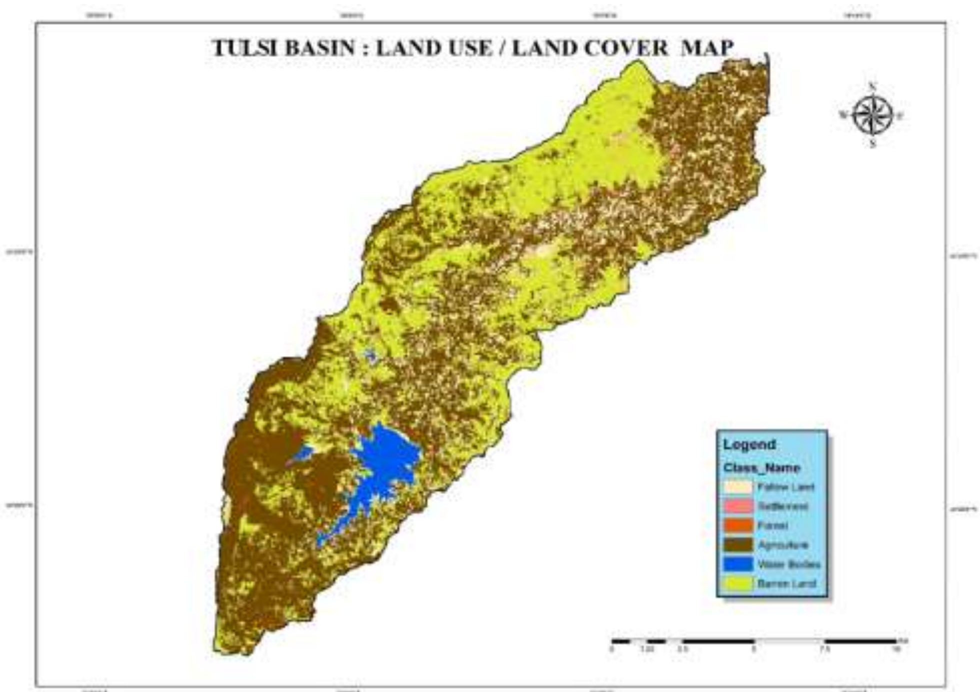

Figure 7: Land use / Land Cover Map

Six land use/land cover (LULC) types were established in this study to determine the geographicdistribution of the support practice factor (P) as shown in Figure 7. These classes are extracted from the IRS LISS-IV (5.8m) satellite data. The land use categories identified are: (1) Barren Land, (2) Agricultural Land, (3) Dense Scrub Forest, (4) Fallow Land, (5) Water Bodies, and (6) Settlements. These classifications formed the framework for scoring land categories for P factor values, under the assumption that each land cover type has a characteristic level of conservation support.

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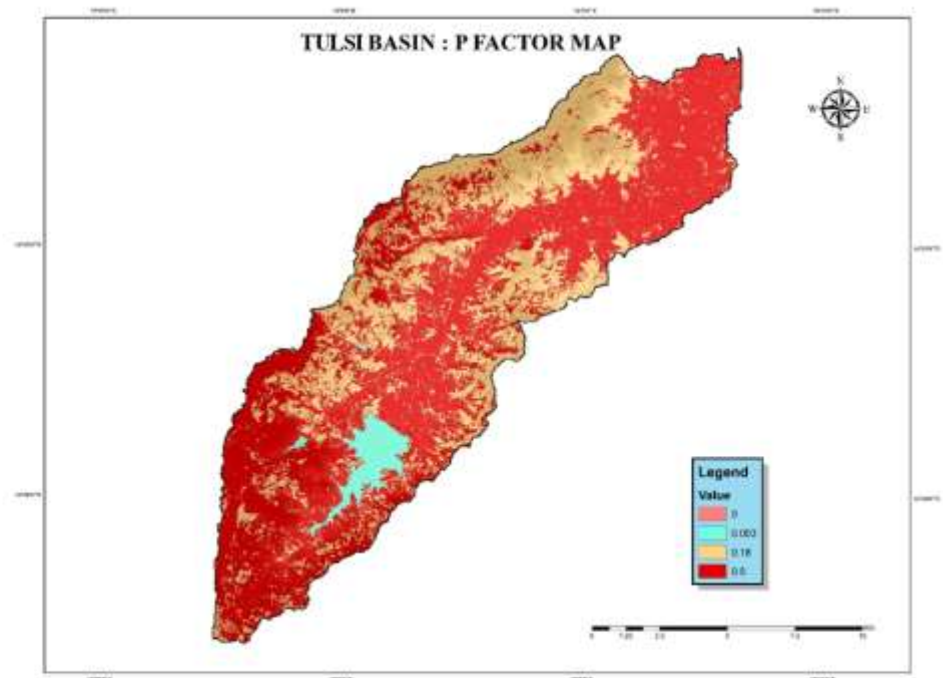

Figure 8: Conversation Support Practice Factor (P)

4. ANNUAL AVERAGE SOIL LOSS

The **Revised Universal Soil Loss Equation (RUSLE)** is an empirical model used to estimate **average yearly loss of soil** due to sheet and rill erosion from rainfall and surface runoff. The soil loss is stated in **tons per hectare per year (t/ha/yr)**.The main aim of this research is to utilise RUSLE to calculate annual average soil loss to the Tulasi river watershed. The soil map as shown in figure 9 reflects that the total watershed average soil loss was 4.64 t / ha / year. The map was classified into two different levels of erosion risks according to the obtained value lie in between 0 – 15 ton/hec/yr.

Table 2 shows the predicted annual soil erosion values for the Tulasi River Basin's five sub-watersheds, TB-1 through TB-5. These figures are based on the results of the RUSLE model, which takes into account a number of variables that affect soil erosion. For each sub-watershed, the Annual Soil Erosion column gives the output value of soil loss, which is likely expressed in tons per hectare per year. In terms of erosion rates, TB-3 is the sub-watershed with the worst record (15.21 t/ha/yr), whereas TB-1 has the best record (0.41 t/ha/yr). Over the whole Tulasi Basin, an estimated 23.22 t/ha/year of soil is lost each year.

10.48047/jocaaa.2024.33.02.30

Table 2: Annual Soil Erosion for different Tulasi sub-watershed.

Basin	Area in sqkm	R-Factor	K-Factor	LS-Factor	C-Factor	P-Factor	Annual Soil Erosion
TB-1	47	1276.9	0.14	0.57	0.008	0.5	0.407586
TB -2	30	1168	0.14	0.52	0.08	0.18	1.224438
TB -3	19	1131.7	0.14	0.32	0.6	0.5	15.21005
TB -4	14	1168	0.14	0.20	0.08	0.5	1.30816
TB -5	55	805	0.36	0.07	0.5	0.5	5.0715
						Total	**23.22**

Table 3 presents the classification of overall the Tulasi watershed area into three different classes depending upon annual soil loss intensity. The 'slight' erosion class (ie with soil loss between 0-1 tonne/ha/year) is the largest covering 47 sq. km, accounting for 28.48% of the whole catchment. The category of moderate erosion, which involves soil loss of 1 to 5 tons per hectare per year, covers 44 sq. sq. km, constituting 26.66 per cent of the total area. The largest category is severe, with soil loss in excess of 5 tons per hectare per year, covering 74 sq. km or 44.84% of the basin. This categorization provides easy spatial interpretation from the basin down to the erosion process in the basin with an indication of areas with higher erosion in the watershed, indicating high priority area with erosion that warrants a focus for soil conservation and watershed management.

Table 3: Tulasi Watershed: Annual Soil Loss Estimation (Ton /ha/Year)

Sr. No.	Soil Erosion	Soil Loss Categories	Area (Sq. Km)	Percentage
1	Slight	0-1	47	28.48
2	Moderate	1-5	44	26.66
3	Severe	>5	74	44.84

10.48047/jocaaa.2024.33.02.30

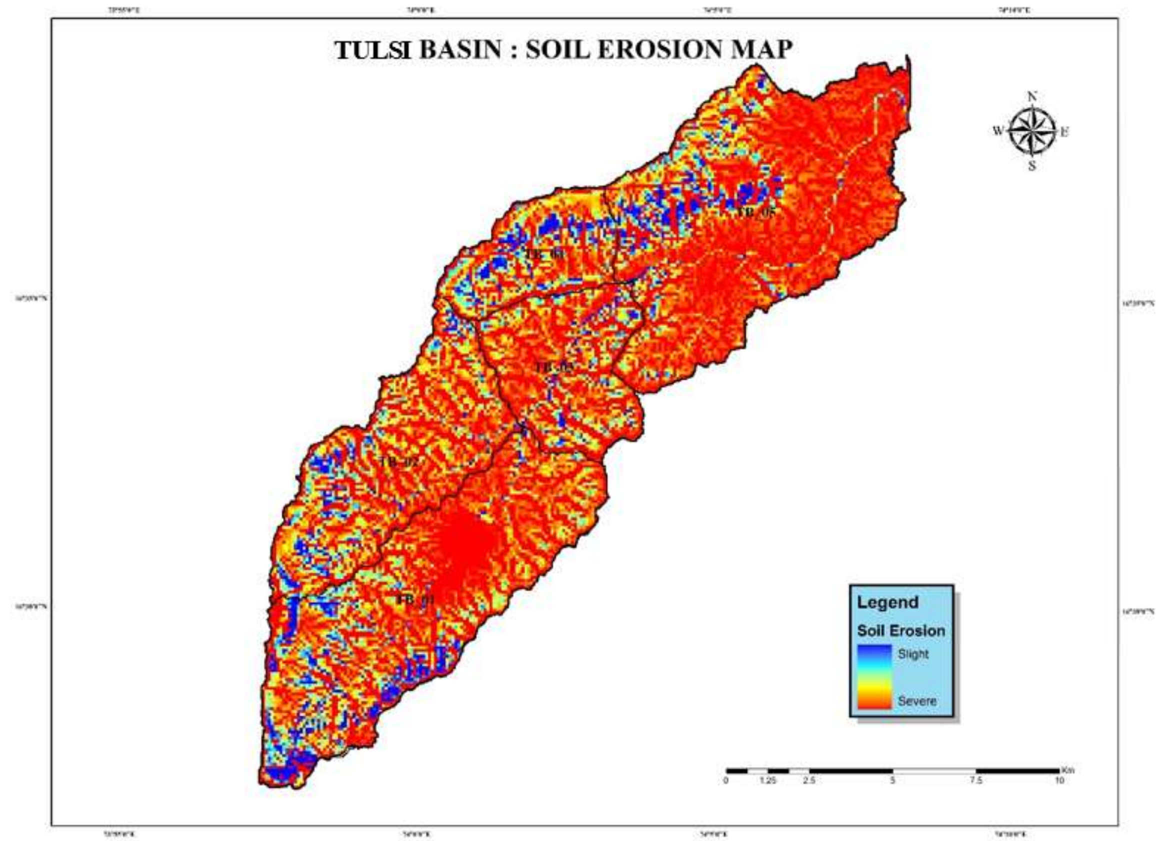

Figure 9: Annual Soil Loss Erosion Estimation Map

5. CONCLUSION

In the current research, theme layers were produced and RUSLE model is applied to estimate soil erosion. The average annual soil erosion in the study area were estimated in accordance with a series of factors of rainfall-runoff, soil erodibility, slope length and slope steepness, cover factor and, conservation factor. Erosion of the soil was frequent in cultivated, fallowed and barren lands. In contrast, hills, dense and sparse forest, villages, brush and barren ground were determined to have a low risk of soil erosion. Based on the soil loss map for the study area, there is a little area (28.48% or 47 sq km) that is predicted not to experienced erosion, a large area (that constituted about 26.666% of the total study area) was predicted to received only slight risk of erosion (1-5 kg hec/yr). On the other hand, the sloped regions are very severe area (44.84%).

In the present study, estimation of soil erosion and soil loss has explained the amount of erosion and area which are affected under certain classes. The research shows that the rainfall erosivity, and slope gradient factors is more responsible for high soil loss. Hence, the decision makers and planners should implement long and short-term management for soil conservation in the erosion prone areas. High soil erosion areas should be given first priority for the implementation of soil conservation and soil managements. Various Conservation measures like building retaining wall,

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check dam, afforestation, adopting contour ploughing and terrace farming method must promote in the local farming communities to minimize the soil erosion.

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