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Geospatial Assessment of Soil Erosion Using Revised Universal Soil Loss Equation in Hirshabelle State of Somalia

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ABSTRACT

The objective of this study is to provide a thorough assessment of soil erosion in the Hirshabelle state from 2020 to 2023, utilizing the Revised Universal Soil Loss Equation (RUSLE) and advanced geospatial technologies, particularly Google Earth Engine, to guide sustainable land management strategies. The study integrates multiple datasets, including CHIRPS for rainfall measurement, MODIS for land use analysis, and a digital elevation model for slope calculation, to offer a comprehensive understanding of the factors contributing to soil erosion. The rainfall erosivity (R) factor is calculated using CHIRPS data, while the soil erodibility (K-factor) is derived from the soil dataset. The topographic condition (LS-factor) is computed using the digital elevation model, and the cover-management (C) and support practice (P) factors are determined from the NDVI and land use data, respectively. The findings reveal considerable spatial variation in soil erosion across the Hirshabelle state. The results are categorized into five levels based on the severity of soil loss: very low (<5), low (5-10), moderate (10-20), high (20-40), and very high (≥40). While areas classified under "very low" soil loss are dominant, indicating relatively stable soils, regions under "very high" soil loss signal potential land degradation and the need for immediate intervention. Furthermore, the study revealed the intricate interplay of slope, vegetation, and land use in influencing soil erosion. Areas with steeper slopes and less vegetation were more susceptible to soil loss, emphasizing the need for targeted soil conservation measures in these regions. The land use factor played a crucial role, with certain land uses contributing more to soil erosion than others.

INTRODUCTION

Soil erosion in Somalia is one of the most concerning issues, and it affects the environment, society, and economy (Oshunsanya & Nwosu 2017). A lack of vegetation in Somalia triggers another kind of degradation of the land, which was shown through the sources (Omuto et al. 2011). Soil erosion is the dominant cause of land degradation in today's sub-Saharan Africa, affecting agricultural productivity on a large scale (Karamage et al. 2016). Soil erosion is very common and causes significant damage, according to several studies and research conducted in several areas of the world (Bou-imajjane & Belfoul 2020). It has become a serious and sustained crisis in Somalia. Further, the issue has some devastating implications for the natural environment and agriculture (Yan et al. 2022). The loss of vegetation is one of the reasons for the loss of soil in Somalia (Omuto et al. 2011). Thus, the study is meant to understand the extent and impact of soil erosion in Somalia. The researchers look forward to figuring out the causes and impacts of the same. A suitable approach to achieve the target is to characterize the dynamics of the vegetation cover. Then, the researchers seeded up to get the complete details and the value of the rate of land degradation due to soil erosion in Somalia. Soil erosion in Somalia is driven by the removal of vegetation cover, unsuitable land use practices, and urbanization, significantly exacerbating land degradation across the country (Nur et al. 2024). Such issues are often analyzed through advanced models and remote sensing tools, as demonstrated by the application of RUSLE to measure erosion and sedimentation (Alexiou et al. 2023). In East Africa, the impacts of climate change on soil erosion have been highlighted using convection-permitting climate models, emphasizing the region's vulnerability to increased erosion rates due to shifting rainfall patterns (Chapman et al. 2021). Remote sensing and geographic information systems (GIS) are critical for evaluating soil loss, sediment yield, and watershed prioritization, even in data-poor regions

(Dhaloiya et al. 2021; Patil et al. 2021). High-resolution satellite missions like Sentinel-2 offer valuable data for assessing vegetation and soil conditions, facilitating erosion monitoring and management strategies (Drusch et al. 2012). Additionally, indices like the Normalized Difference Vegetation Index (NDVI) can estimate sediment production and contribute to understanding vegetation's protective role against erosion (Lense et al. 2020).

The integration of these methodologies underscores the importance of modern tools and models in managing erosion, with specific emphasis on adapting practices to mitigate nutrient losses and ensure sustainable land management in vulnerable regions like Somalia (Chen et al. 2017; Yebra et al. 2008).

Erosion of soil is a vital environmental issue that affects multiple sites across the world (Bou-imajjane & Belfoul 2020). Soil erosion means the removal of soil in excessive quantity by various agents of erosion. Soil degradation can assume the following forms: water erosion, wind erosion, mass motion, salt excess, physical degradation, biological degradation, and chemical degradation (Abidin et al. 2021). Soil erosion can lead to a decrease in the health and productivity of agricultural lands. It is also considered to be a major threat to the natural environment (Ailincăi et al. 2011). When soil erosion is not wisely controlled and prevented, It results in significant damage to agriculture and ecosystems. The decline in soil fertility is attributed to soil erosion. Erosion causes a decline in productivity as erosion leads to physical, chemical, and biological degradation (Gaonkar et al. 2024). Soil erosion acts as the causative factor and the outcomes of land degradation (Afriyie et al. 2020). It is important to remember that soil erosion can happen in plenty of different ways. Splash erosion, sheet erosion, rill erosion, and gully erosion all take part in soil erosion (Vrieling et al. 2005). These processes are mostly caused by deforestation, urbanization, and the intensification of agriculture. Also, the worthiest land degradation problem in the whole world is water-induced soil erosion (Vrieling et al. 2005). This is a severe concern that needs watershed management interventions to avoid further stint and protect ecosystem health (Tegegne et al. 2022).

As stated in various study findings, soil erosion directly impacts its fertility. Erosion in agriculture production, infrastructure, and water quality has various negative ecological effects. The outcome of the process of water erosion causes a severe reduction in the fertility of the soil by physical, chemical, and biological degradation (Ailincăi et al. 2011). To produce valuable insights and improve our understanding of the critical factors that govern erosion and sediment transport to different places, either stronger or weaker than ever (Tegegne et al. 2022). Soil erosion is a major environmental issue with crop-specific afflicts and land degradation (Ailincăi et al. 2011). Concentrating on suitable land management practices and constant monitoring of susceptible areas is important to prevent and control erosion (Puente et al. 2019). Implementing appropriate management strategies is critical, with severe soil erosion and its outcomes. To make this happen, efforts to preserve the soil must be undertaken once the severity of the issue is well comprehended (Tamene et al. 2006). Wischmeier & Smith's (1978) Universal Soil Loss Equation (USLE) was developed back in 1978 (Wischmeier & Smith 1978). It is one empirical model of soil erosion. It is used by most technicians to predict soil loss due to water erosion (Vezina et al. 2006, Trinh 2015, Nguyen 2011, Mc Cool et al. 1987). Remote sensing and GIS simulation are utilized to estimate and map the annual water erosion rate spatial pattern utilizing the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997). Earlier research into soil erosion forces had primarily focused on empirical models, physical properties-based models, nuclear tracing, and then spatial distributed multivariate models (Wang et al. 2016). The RUSLE model is a very easy-to-understand formula, needs only a few parameters, and is very accurate compared to other models (Wang & Zhao 2020). As viewed from the literature, this model is widely used and provides excellent results in predicting soil erosion (Stathopoulos et al. 2017, Rocha & Sparovek 2021, Wang & Zhao 2020). Previous studies have shown the application and widespread use to estimate cropland soil erosion at the watershed, regional, and global scales (Cui et al. 2022). It can also find the clear-cut cost and feasibility of controlling soil erosion (Orchard 2021). The accuracy with which the RUSLE model could predict the rate and spatial distribution of soil erosion using remote sensing data had been estimated in a study in China (Hua et al. 2019). Making the remote sensing data included in the RUSLE model to determine the rate of erosion of soil is user-friendly for studying the spatial distribution of erosion of soil (Orchard 2021). The above-mentioned studies, including the GIS and remote sensing techniques, have provided elaborate data about the surface and thereby had higher accuracy along with the spatial resolution for the estimation of soil erosion. These are the studies that state that GIS and remote sensing give an upper hand in getting a detailed estimation of soil erosion in a specific land area (Chala 2019). By integrating the RUSLE model with Remote sensing and GIS mapping, researchers developed a way to estimate soil loss and plan appropriate soil conservation strategies. Thus, keeping in mind the aforementioned discussion, this study aims to measure the amount of soil loss from the Hirshabelle area using the RUSLE model with the integration of GIS and remote sensing techniques.

MATERIALS AND METHODS

Study Area

Hirshabelle, officially known as Hirshabelle State of Somalia (Latitude: 3.8793° N, Longitude: 45.9040° E), is a Federal Member State in south-central Somalia (Fig. 1). It has a border with the Galmudug State in the north, the Southwest State of Somalia and Banadir region to the south, Ethiopia to the west, and the Indian Ocean to the east (Wikipedia 2018). The state is encompassed by two regions: Hiraan and Middle Shebelle (European Union Agency for Asylum 2011). Furthermore, the region confronts adverse environmental challenges, including flash flooding and short-lived, seasonal flooding. The most likely flash flood areas are Beledweyne, Jalalaqsi, Bulo Burde, Mahaday, and Jowhar. These floods are intense but brief and occur seasonally (United Nations Environment Programme 2022).

RUSLE Model

Using a combination of remote sensing and GIS, the RUSLE model was utilized to map and identify soil erosion risk regions in Hirshabelle and calculate the mean annual soil loss rate (t/ha/year) on a cell-by-cell basis. The following was constructed and discussed after raster maps of each RUSLE parameter obtained from several data sources. This model works on all continents where soil erosion due to water erosion is an issue (Laflen et al. 2003). The model can be expressed as:

$$A = R \times K \times LS \times C \times P$$

Where, A=average soil loss per unit of area (t/ha/year); R=rainfall erosivity factor (MJ mm ha^{-1} h^{-1} y^{-1}); K=is the soil erodibility factor (t h MJ^{-1} mm^{-1}); LS=topographic factor (dimensionless) including slope length (L) and steepness (S) factors; C=cover management (dimensionless); and P=support (or conservation) practice factor (dimensionless). The schematic representation of the RUSLE model is presented in Fig. 2.

Rainfall Erosivity (R-factor)

The Rainfall Erosivity (R-factor) is a key parameter in the RUSLE (Revised Universal Soil Loss Equation) model, representing the impact of rainfall intensity on soil erosion (Wagari & Tamiru 2021). It is calculated by multiplying the total kinetic energy of a rainfall event by its maximum 30-minute intensity. This factor serves as an index for assessing the potential erosive power of rainfall, enabling predictions of soil erosion risks (Mikhailova et al. 1997). Accurate computation of the R-factor helps to estimate and manage soil erosion in areas where there is a lack of time-series precipitation data. In such cases, monthly satellite precipitation data can be used to determine average annual erosivity (Pandey & Gautam 2015). Thus, estimating precipitation erosivity is crucial in data-scarce regions and can be achieved using various methods, leveraging precipitation erosivity data and satellite-based precipitation.

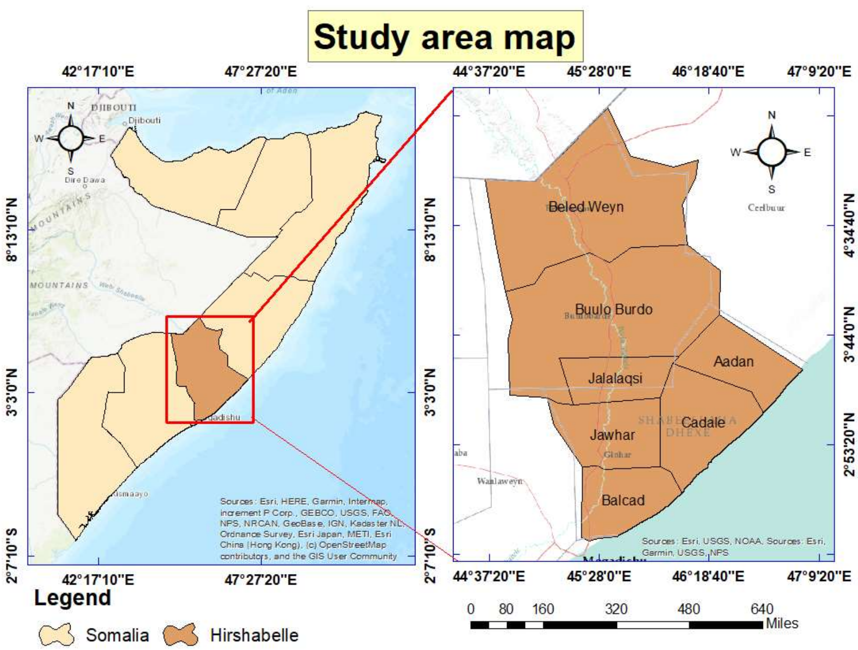

Fig. 1: Map of the study area.

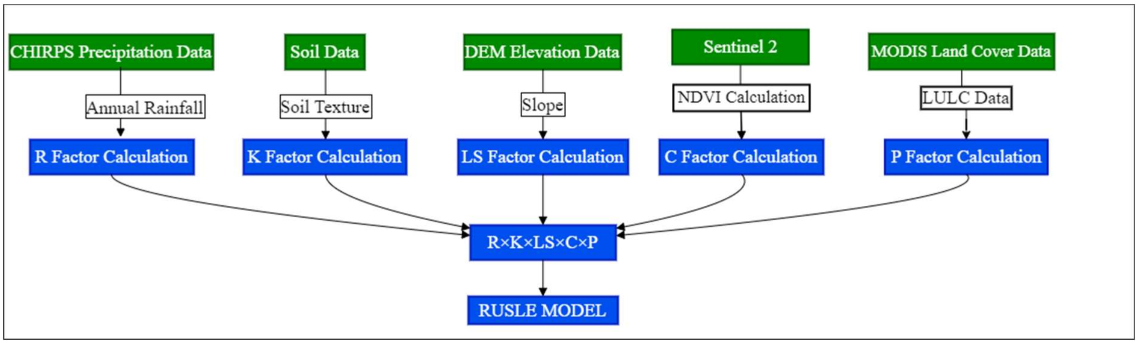

Fig. 2: Flow diagram of the methodology.

Soil Erodibility (K-factor)

The K-factor is critical in calculating sediment detachment and distribution on a region's surface (Veith et al. 2017). It represents the resistance of soil to erosion when impacted by raindrop impact and concentrated flow, as defined by the RUSLE model (Bayramin et al. 2007). This factor reflects soil erodibility and helps quantify how changes in ecosystems or land management practices can reduce erosion susceptibility. In the RUSLE model, the K-factor estimates soil erosion potential based on various soil parameters, including soil texture, organic matter, and water content. Several modified algorithms exist to calculate the soil erodibility factor for different soils at specific sites (Rodrigo-Comino et al. 2020).

Slope Length and Steepness Factors (LS)

Slope length and steepness are the main topographical factors affecting soil erosion. According to Ozsoy & Aksoy (2015), erosion rates-whether water or soil erosion-are directly dependent on flow velocity. Erosion occurs at a higher rate on longer slopes (Dudiak et al. 2019). Steeper slopes gain less energy from water flowing down, leading to more significant soil displacement. In the RUSLE model, the LS factor is a dimensionless parameter that identifies variations in soil erosion intensity proportional to slope length and steepness. This factor effectively predicts and controls erosion threats by considering the slope's impact (Gashaw et al. 2017). Studies, for example, Prasannakumar et al. (2012), highlight the importance of the LS factor in understanding soil erosion risk based on slope characteristics.

Land Cover Management Factor (C-factor)

The C-factor in the RUSLE model is an important parameter that measures soil loss based on land cover, crops, and treatment practices (Gashaw et al. 2017). It is a dimensionless quantity indicating the reduction in soil loss per unit area due to specific land use practices. Monitoring or estimating soil loss due to plant cover and residual matter and evaluating efficiency levels in relation to farmland management are necessary for determining potential mitigation methods and durations (Saha 2018, Zhao et al. 2012). Different types of vegetation, structural canopies, and management strategies significantly influence soil loss and erosion rates, as defined by the C-factor.

Support Practice Factor (P-factor)

The P-factor in the RUSLE model represents the effectiveness of soil conservation practices in reducing erosion. It is calculated by dividing soil loss from a particular support practice by the soil loss from up-and-down slope cultivation (Renard et al. 1997).

Data for Estimation of Soil Erosion by RUSLE Model

Rainfall and Runoff Erosivity factor (R-factor), Soil Erodibility factor (K-factor), Topographic factor (LS-factor), Crop management factor (C-factor), and Support practice factor (P-factor) were the factors for the estimation of soil erosion by RUSLE model. The R-factor was calculated using the total precipitation data derived from CHIRPS for the particular study period. The output finally obtained was first widely multiplied by 0.363, and then 79 was added to convert the total rainfall amount given into an erosive factor. Similarly, the K-factor was calculated from the regional soil dataset. The LS factor was calculated using the DEM data. The slope percent was calculated, and the LS factor was then calculated. The C-factor was calculated using the NDVI (Normalized Difference Vegetation Index) derived from the Sentinel-2 data. Lastly, the P-factor was estimated using the MODIS land-use and land-cover dataset, and the slope percent was calculated.

RESULTS

Rainfall Erosivity (R-factor)

The CHIRPS (Climate Hazards Group InfraRed Precipitation with Station) dataset was used for the measurement of the R-factor. The CHIRPS dataset was filtered for the 'precipitation' band for the particular period of 2020 to 2023. The next step was clipping the data to the boundaries of the Hirshabelle state. The R-factor will ascertain the erosive force of rain and is calculated as follows:

$$R = \text{Precipitation} \times 79 + 0.363$$

This R-factor has been applied to the RUSLE model mentioned by Panagos et al. (2017). The R-factor map of Hirshabelle state is depicted in Fig. 3. For the state the R-factor ranged from 181.535 to 484.344. Hence, these values showed the potential rate of soil loss to rainfall-driven erosion in the Hirshabelle state. The higher the R-factor value, the higher the susceptibility of the area to soil erosion by rainfall.

Soil Erodibility (K-factor)

The K-factor aims to determine the susceptibility of the soil particles to detachment and transport by the action of rainfall and runoff. Several soil values to assess the K-Factor were considered. The special formula and the values used seem to be region-specific, and these values seem to be based on the local soil properties. The values of the K-factor were determined by Wischmeier's procedure (1976). The estimated K factor value ranged from 0 to 0.05. We obtained specific values of 0, 0.02, 0.034, 0.042 and 0.05. These values of the K-factor provide a measure of how susceptible the soil is to erosion, and the higher the value, the more erodible the soil; in other words, higher K-values indicate places where the soil is more susceptible to erosion. Therefore, these areas are anticipated to require soil conservation procedures to stop considerable loss of soil from erosion. In contrast, for areas of lower K-values, less erosion control methods can be used. The K-factor map of the Hirshabelle state is given in Fig. 4.

Slope Length and Steepness Factors (LS-factor)

The slope was calculated from the "elevation" attribute of the digital elevation model (DEM). Then, the slope was converted from degrees to percent using the following formula:

$$\text{Slope } (\%) = \tan(\text{slope in degrees}) \times 100.$$

Then, the LS factor was calculated using the following formula (Desmet & Govers 1996):

$$LS = (\text{Slope } 0.53 + \text{Slope}^2\ 0.076 + 0.76) \times \sqrt{(500/100)}$$

This equation is used to find the potential soil erosion with the combined impact of slope steepness and the influence of slope length. In the LS equation, ($\text{Slope} \times 0.53 + \text{Slope}^2 \times 0.076 + 0.76$) refers to the effect of slope on erosion, including both linear and quadratic effects of slope, whereas

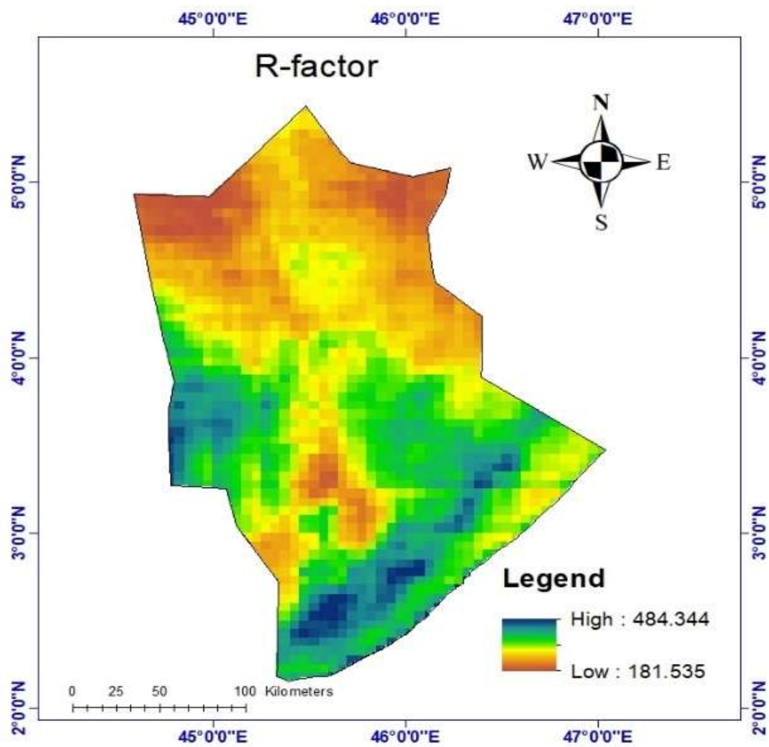

Fig. 3: Rainfall erosivity (R-factor) map of Hirshabelle state.

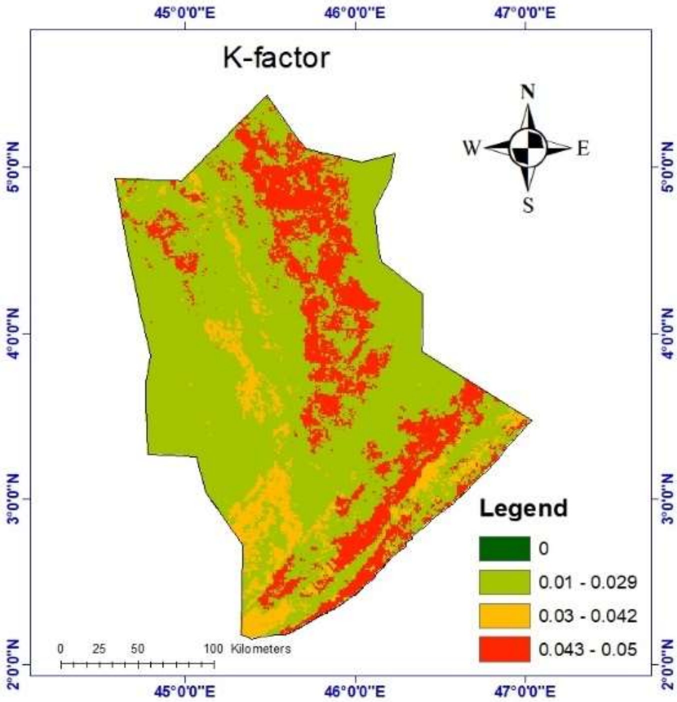

Fig. 4: Soil erodibility (K-factor) map of Hirshabelle state.

$\sqrt{(500/100)}$ represents the interference of the slope length. The square root in this function also represents a nonlinear relationship. Fig. 5 shows the steepness of the landscape slopes of the different parts of the study area, which varies from 0 (flat area) to 9.4642 (extremely steep area).

The LS factor map suggests that soil is likely to erode due to both steepness and slope length. The values of the LS factor ranged from 1.69941 (low erosion potential) to 28.1295 (high erosion potential). The map of the LS factor of Hirshabelle state is given in Fig. 6.

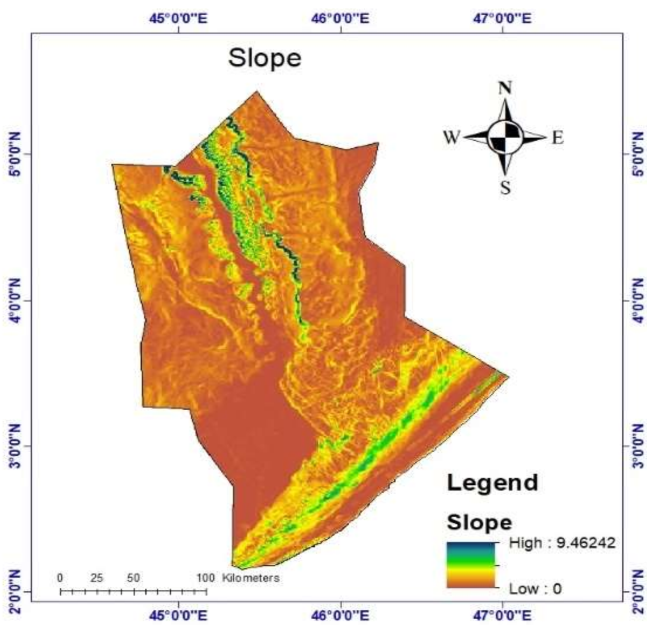

Fig. 5: Slope map of Hirshabelle state.

Normalized Difference Vegetation Index (NDVI)

The current study focuses on the Normalized Difference Vegetation Index (NDVI) and the C-factor in erosion smoothing facts. These two indispensable metrics are analyzed for the environmental and agricultural study. The Normalized Difference Vegetation Index (NDVI) is the most important vegetation index that is capable of assisting the studying scientists in estimating the vegetation health, biomass, and canopy of the land site (Li et al. 2020). It is also a straightforward graphical indicator of the measurement that consists of the metrics from the distant remote sensors. This index can provide the measurement of whether the categories that are considered for studies have resulted in any live green that is essential (Pahlevan et al. 2022). The calculation of NDVI is computed utilizing the following formula (Sarmin et al. 2023):

$$NDVI = (NIR - RED) / (NIR + RED)$$

The NDVI or Normalized Difference Vegetation Index is calculated using Band 8 (NIR) and Band 4 (RED) of the Sentinel-2 satellite (Sarmin et al. 2023). The ratio of these bands is the formula to get the NDVI and helps in understanding the health and coverage of vegetation (Reiche et al. 2018). Through the understanding of environmental landscapes provided by NDVI, soil conservation, and sustainable agriculture can be planned more accurately (Zhang et al. 2016). Hence, two crucial tools in environmental and agricultural studies are NDVI and the C-factor. The outcome of the NDVI image after the clipping for Hirshabelle state was used to find the median value, and the values of NDVI ranged from -0.2 to 0.3. The negative value of NDVI corresponds to water, i.e., values closer to -1. Whereas close to zero (i.e., (-0.1 to 0.1)) relates to barren or open areas of rock, sand, or snow, and the higher value of NDVI (0.3 to 0.8) has temperate or tropical rainforests or areas with dense vegetation growth. The map of NDVI of Hirshabelle state is given in Fig. 7.

Vegetation Cover Management (C-factor)

C-factor represents the effect of cropping and management practices on erosion rates. The code is to calculate the C factor using NDVI derived from Sentinel-2 data. The presence of green vegetation is represented by the NDVI, as derived from the Sentinel-2 data. The specific formula seems to be derived from the transformation of the NDVI values, which is a commonly applied technique of the remote sensing study based on the C-factor Model. Fig. 8 represents the C-factor map of the study area. The values of the C-factor ranged from 0 to 1. The C-factor is the ratio between the erosion magnitude of a certain area with specific vegetation cover and crop management to the erosion magnitude of identical soil without vegetation. Hence, the understanding of NDVI and C-factor analysis can give more insight into the health of vegetation and the risk of soil erosion. The NDVI value shows substantial vegetation cover, and the C-factor model suggests that the erosion rate is significant because of this vegetation.

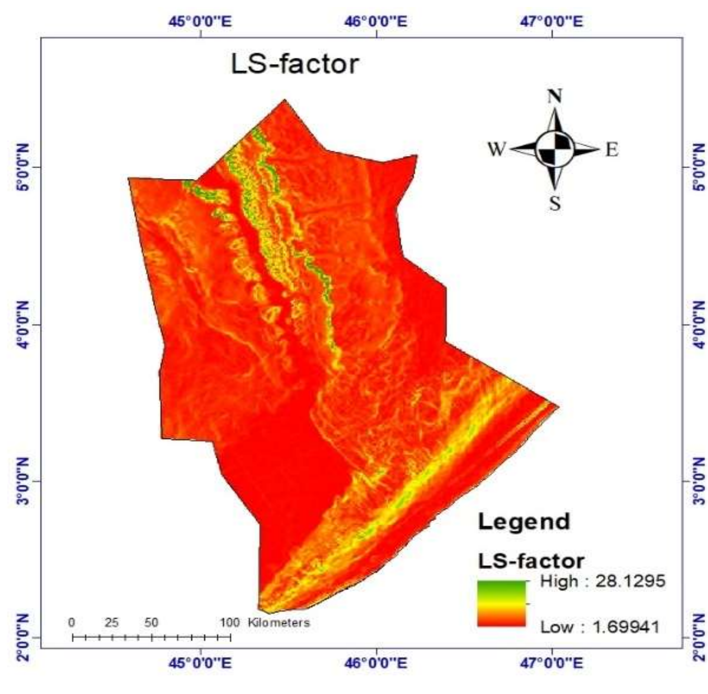

Fig. 6: LS factor map of Hirshabelle state.

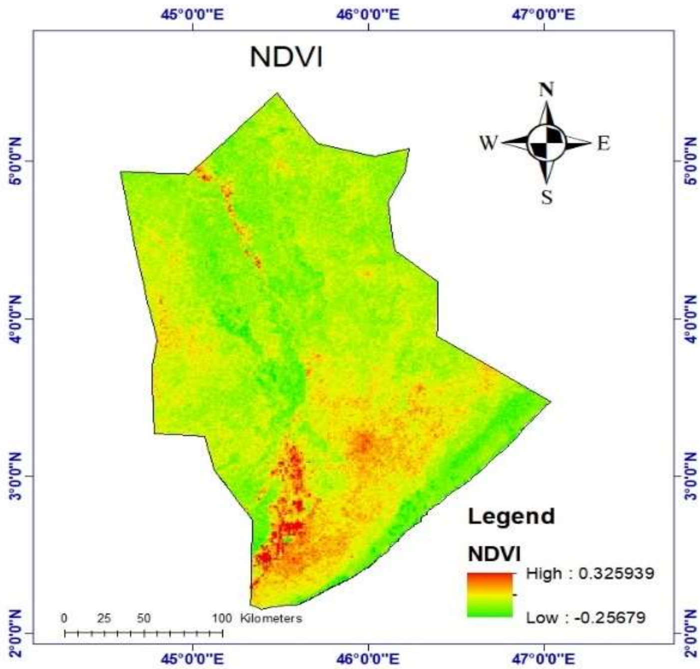

Fig. 7: NDVI map of Hirshabelle state.

Support Practice (P-factor)

The major goal of the P-factor is to account for the effect of erosion-control practices on soil loss. Based on the type of land cover from MODIS data, the slope determines the P-factor. The specific rules that are followed are expected to be region-specific and may be based on local land management practices (Dabney et al. 2012). The P-factor is the ratio of soil loss for a specific support practice to soil loss for up-and-down slope cultivation on the same type of land cover. It quantifies

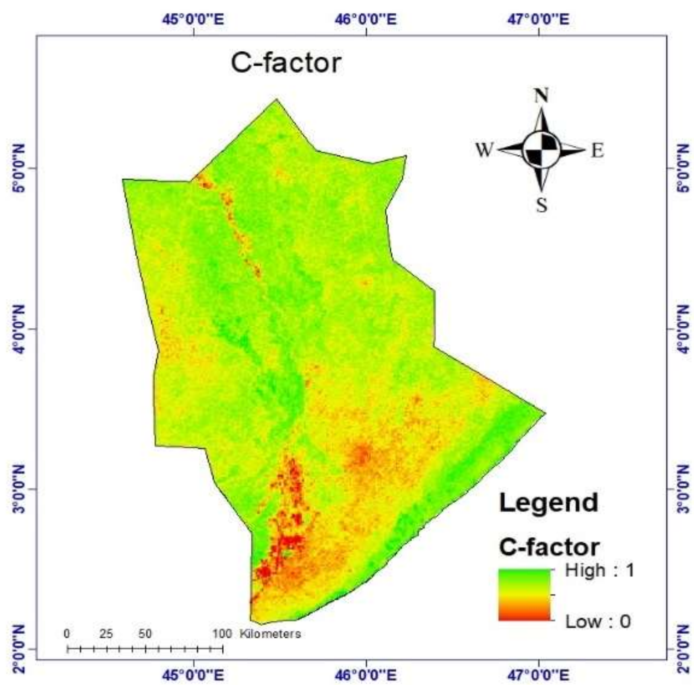

Fig. 8: C-factor map of Hirshabelle state.

the effectiveness of the various conservation practices like contour plowing or terracing. The P-factor analysis of the study area provides valuable information about the effectiveness of soil conservation practices in the area. The P-factor values of the study area (Fig. 9) range from 0.6 to 1. The lower P-factor values nearer to 0.5 indicate that the conservation practices are highly effective in preventing soil erosion. While higher P-factor values, approximately up to 1, indicate less effective practices in place or no erosion control measures are in place in the area.

Soil Loss

Soil loss was estimated using the Revised Universal Soil Loss Equation (RUSLE). The final soil loss was calculated by multiplying R, K, LS, C, and P factors. The mean values of the factors of the RUSLE model are presented in Table 1.

The soil loss analysis offers a comprehensive view of areas at risk of erosion within the defined area. The soil loss map illustrates the varying degrees of soil loss, with areas falling into one of five categories: "very low," "low," "moderate," "high," and "very high," following Housseyn et al. (2021). The distribution of areas according to soil loss classes is presented in Table 2 and depicted in Fig. 10.

DISCUSSION

The estimation of the R-factor, starting from 181.535 to a high of 484.344 (Fig. 3), suggests the variability of the potentiality of soil loss because of rainfall-triggered erosion. The better R-factor values point in the direction of areas that are greater at risk of soil erosion due to rainfall, suggesting the need for focused interventions in those regions to mitigate erosion (Fenta et al. 2020). Similarly, the computed K-factor values, starting from 0 to 0.05 (Fig. 4), offer insights into the soil's susceptibility to erosion. The higher K-values endorse areas with extra erodible soils, indicating the need for particular soil conservation measures to save excessive soil loss (Angima et al. 2003). Conversely, regions with lower K-values, signifying less erodible soils, may additionally require less extensive conservation practices. The LS-factor map (Fig. 5 and Fig. 6) highlights the capacity for soil erosion because of the combined impact of slope period and steepness. This issue is of unique importance, as regions with a high LS factor represent regions with a higher chance of soil erosion, underlining the need for tailored erosion management techniques in such regions

Table 1: Mean Values of the RUSLE Model.

Parameters	Mean Values
Mean R Factor	338.3558311
Mean K Factor	0.032564672
Mean LS Factor	2.456259309
Mean C Factor	0.370976513
Mean P Factor	0.801867416
Mean Soil Loss	8.202920923

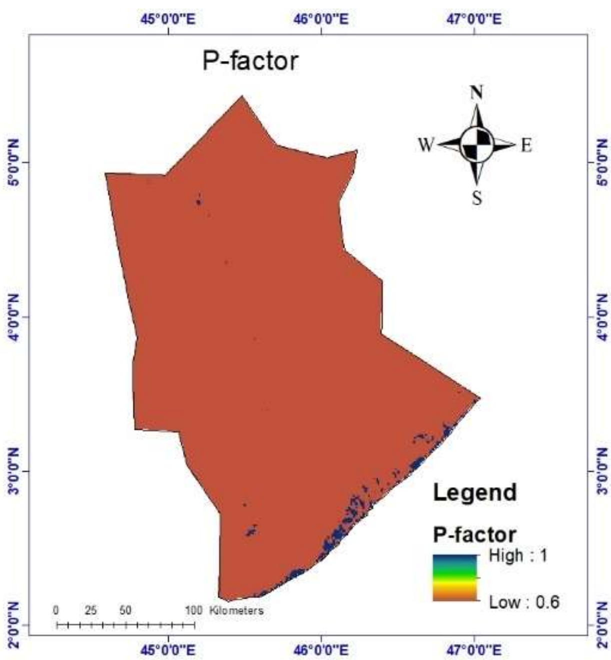

Fig. 9: P-factor map of Hirshabelle state.

Table 2: Distribution of soil loss classes along with their respective areas.

Categories	Area in hectare	Proportion of the total area (%)
Very low (Soil loss < 5)	1,005,247.882	19.11%
Low (Soil loss 5-10)	3,001,216.756	57.04%
Moderate (Soil loss 10-20)	1,089,858.46	20.71%
High (Soil loss 20-40)	150,108.38	2.85%
Very high (Soil loss ≥ 40)	14,884.63	0.28%

(Moses 2017). The NDVI evaluation (Fig. 7) and derived C-factor (Fig. 8) provide valuable insights into the country of plant life and its position in soil erosion in the high NDVI and C-factor derived from NDVI, presenting massive protection in opposition to soil erosion (Kogo et al. 2020). The P-factor values, ranging from 0.6 to 1 (Fig. 9), offer an indication of the efficacy of conservation practices within the vicinity. Lower P-factor values advocate that modern conservation practices are powerful at stopping soil erosion, while better values represent areas in which more efficient erosion management measures may also need to be carried out (Amsalu & Mengaw 2014). The final soil loss estimation derived from the product of R, K, LS, C, and P factors offers a comprehensive representation of the areas at risk of erosion within the Hirshabelle state (Fig. 10). The categorization of soil loss into “very low,” “low,” “moderate,” “high,” and “very high” provides a clear understanding of the severity of soil erosion in different areas (Yesuph et al. 2021). The study assessed soil erosion risks in northwest Somalia, revealing that most of the area faces moderate erosion risk. The northern region, including Bossaso and other weather stations, demonstrates low erosivity risk due to lower annual precipitation. In contrast, southern regions, despite their steep slopes, experience higher erosion risk. These findings highlight the critical influence of precipitation and topography on soil erosion in the Hirshabelle state (Nur et al. 2024).

CONCLUSIONS

An extensive study on soil erosion in the Hirshabelle state offers vital insights into the various reasons that trigger soil loss. The primary factors that stimulate soil loss in a region are, namely, erosivity of rainfall, erodibility of soil, length, and steepness of slopes, the cover of vegetation, and support practices. Soil loss risk for the Hirshabelle area is estimated using a Revised Universal Soil Loss Equation (RUSLE). CHIRPS, MODIS, Sentinel-2, and a local soil dataset are used to predict soil loss risk and erosion for the area. Results from the NDVI and C-factor study show the importance of the presence of vegetation in the prevention of soil erosion. The study also brings out the significance of increasing and keeping vegetation safe to protect soil. The P-factor study shows that the soil conservation practices carried out in the area are quite efficient. This study also helps improve these practices further. The satellite data combined with the soil runoff models indicate that it offers a valuable and solid foundation for policymakers to make crucial choices about

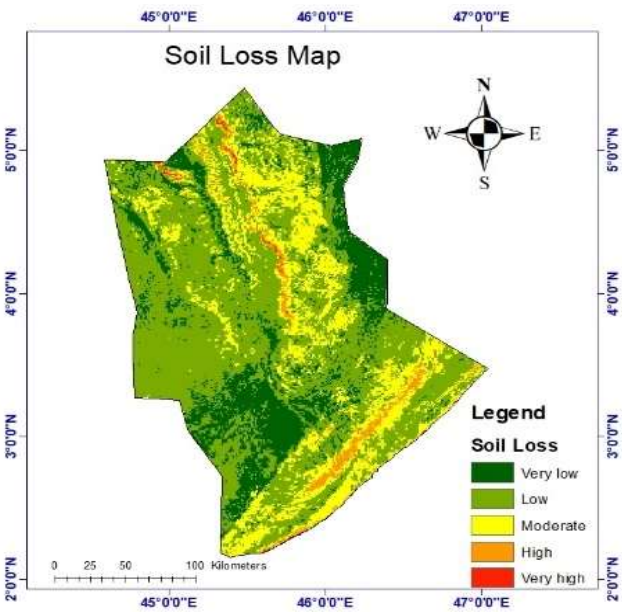

Fig. 10: Soil loss map of Hirshabelle state.

land. The changes associated with soil loss/readiness help to understand and study the areas that are prone to erosion. Since soil is the most important resource and supporting factor, conservation practices will keep the land productive and healthy. Thus, taking measures to prevent soil loss will encourage sustainable land use.

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