East African Scholars Journal of Agriculture and Life Sciences
Abbreviated Key Title: East African Scholars J Agri Life Sci
ISSN 2617-4472 (Print) | ISSN 2617-7277 (Online)
Published By East African Scholars Publisher, Kenya

OPEN ACCESS

Volume-8 | Issue-6 | Jul-2025 | DOI: https://doi.org/10.36349/easjals.2025.v08i06.002

Original Research Article

GIS-Based on Assessment of Soil Erosion in Bay Region of Somalia

Abdiaziz Hassan Nur[1*], Jamal Abdikarim Mohamed[2], Abdourahaman Sahal Hussein[3], Nasreen Sultana Orchy[4]

[1]Program Officer at Zamzam Foundation in Jowhar-Somalia
[2]Lecturer Somali National University, Faculty of Agriculture and Environmental Science
[3]Amoud University
[4]Bangladesh University of Science and Technology

Article History
Received: 24.04.2025
Accepted: 30.05.2025
Published: 22.07.2025

Journal homepage:
http://www.easpublisher.com

Quick Response Code

Abstract: Soil erosion is a major environmental challenge that necessitates meticulous investigation and the implementation of sustainable management practices. The objective of this study is to provide a thorough assessment of soil erosion in the Bay region 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 (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 regions. The results are categorized into five levels based on the severity of soil loss: Slight (<10), Moderate (10-20), High (20-30), very high (30-40), and Severe (>40). While areas classified under "Slight" soil loss are dominant, indicating relatively stable soils, regions under "Severe" 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.

Keywords: Soil Erosion, Bay region, RUSLE, Somalia, Google Earth Engine (GEE), GIS.

INTRODUCTION

Soil erosion in Somalia represents a critical issue with significant environmental, societal, and economic consequences (Oshunsanya & Nwosu, 2017). Soil erosion in Somalia is a critical environmental challenge, driven by a combination of natural factors such as high rainfall erosivity, steep slopes, and anthropogenic activities like deforestation, overgrazing, and unsustainable land use practices (Nur *et al.*, 2024) A lack of vegetation contributes to severe land degradation in the region, as highlighted by various studies (Omuto *et al.*, 2011). The accelerating impacts of climate change have further compounded soil degradation in Somalia, threatening food security and livelihood systems. As highlighted in recent studies, climate-induced changes such as prolonged droughts, erratic rainfall patterns, and extreme weather events significantly challenge sustainable food production and increase the vulnerability of agro-ecological systems (Ibrahim,2024) Across sub-Saharan Africa, soil erosion remains the primary driver of land degradation, severely affecting agricultural productivity on a broad scale (Karamage *et al.*, 2016). Globally, soil erosion is prevalent and has been shown to cause considerable harm, supported by extensive research (Bou-imajjane & Belfoul, 2020). In Somalia, the situation has evolved into a persistent crisis with adverse effects on natural ecosystems and agriculture (Yan *et al.*, 2022). The loss of vegetation is a key factor in soil depletion in Somalia, driven by the removal of plant cover, inappropriate land-use practices, and urban expansion, which collectively accelerate land

***Corresponding Author:** Abdiaziz Hassan Nur
Jazeera University, Faculty of Agricultural Science, Mogadishu, Somalia

degradation (Omuto *et al*., 2011); (Nur *et al*., 2024). To address this issue, researchers have focused on understanding the extent and consequences of soil erosion, emphasizing the need to analyze vegetation cover dynamics. Techniques such as the Revised Universal Soil Loss Equation (RUSLE) and remote sensing tools have proven valuable in evaluating erosion rates and sedimentation patterns (Alexiou *et al.,* 2023). In East Africa, climate change exacerbates soil erosion, with convection-permitting climate models revealing heightened vulnerability due to changing rainfall patterns (Chapman *et al*., 2021). Remote sensing and GIS tools play a pivotal role in assessing soil loss, sediment yield, and watershed prioritization, even in areas with limited data availability (Dhaloiya *et al*., 2021); (Patil *et al.,* 2021). High-resolution satellite missions like Sentinel-2 provide critical information on vegetation and soil conditions, enabling effective erosion monitoring and management (Drusch *et al*., 2012). Indices such as NDVI further assist in evaluating sediment production and highlight vegetation's role in mitigating erosion (Lense *et al*., 2020). These advanced methodologies and tools emphasize the necessity of sustainable land management and adaptive strategies to minimize nutrient loss and ensure long-term land productivity in vulnerable areas 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 and Smith's (1978) Universal Soil Loss Equation (USLE) was developed back in 1978 (Wischmeier and Smith 1978). The integration of Google Earth Engine and remote sensing data, including CHIRPS for rainfall and MODIS for land cover, enhanced the precision of erosion predictions, demonstrating the effectiveness of technology in resource-limited settings (Nur *et al*., 2025). 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 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 Bay area using the RUSLE model with integration of GIS and remote sensing techniques.

MATERIALS AND METHODS

Study Area

The Bay region, an administrative area in southern Somalia situated at latitude 3° 04' 16.80" N and longitude 43° 50' 4.19" E, faces significant challenges due to inter-clan conflicts. According to Barrow (2020), these conflicts are primarily fueled by disputes over land, resources, and political power, particularly within the Baidoa district. The ongoing strife has severely compromised the region's security infrastructure, allowing Al-Shabab militants to maintain control over the outskirts. Furthermore, the area's capacity for livestock production, which holds considerable potential, is significantly undermined by both natural and human-induced constraints (Birhan, 2013).

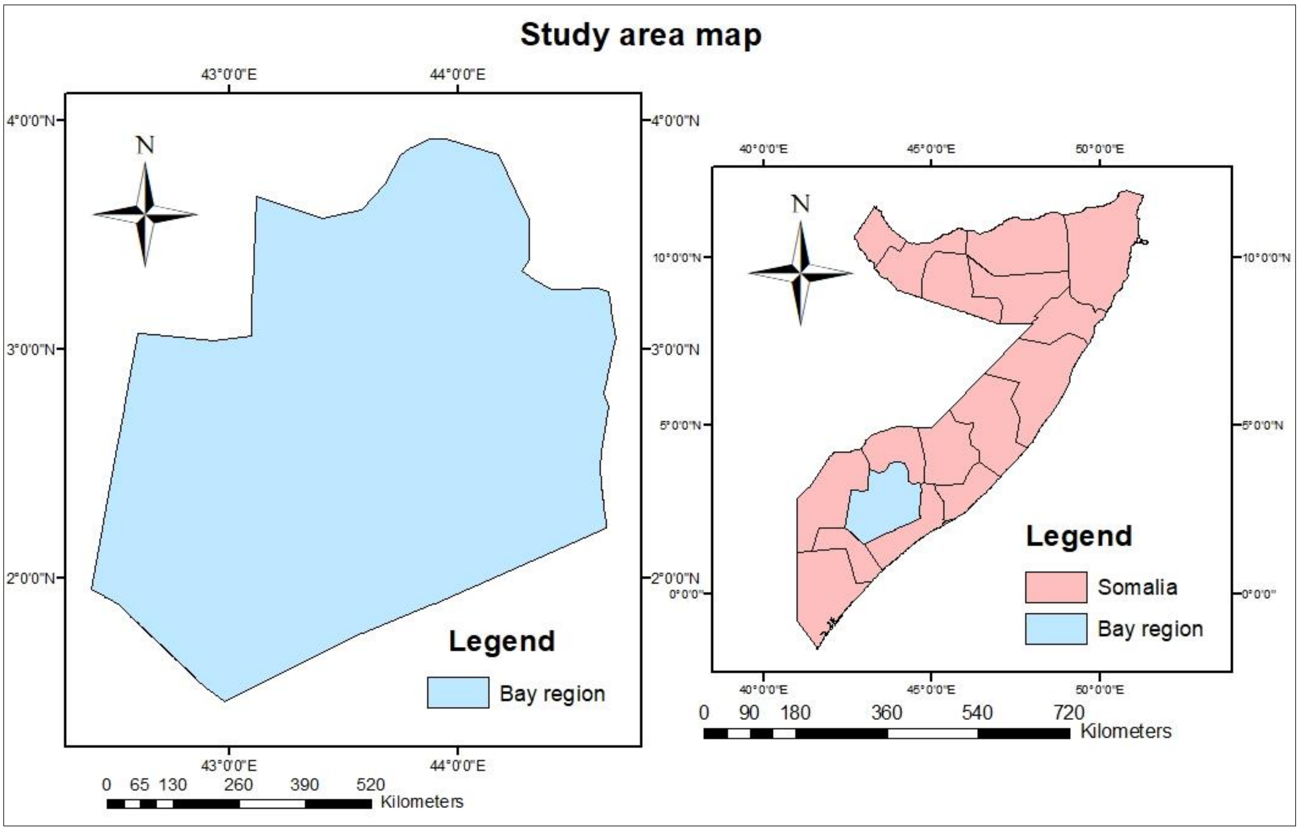

Figure 1: Map of the study area

RUSLE Model

Using a combination of remote sensing and GIS, the RUSLE model was utilized to map and identify soil erosion risk regions in Bay 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 erodibilty 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 Figure 2.

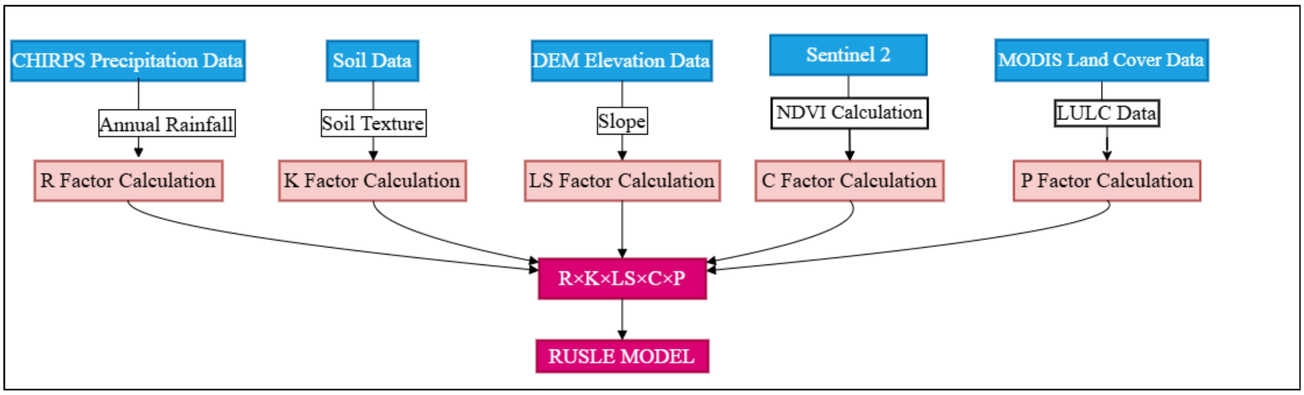

Figure 2: Flow diagram of the methodology

Rainfall Erosivity (R-Factor)

The Rainfall Erosivity (R-factor) is a critical element of the RUSLE model, quantifying the erosive potential of rainfall based on its intensity and kinetic energy (Wagari & Tamiru, 2021). It is determined by multiplying the total kinetic energy of a rainfall event with its maximum 30-minute intensity, providing a reliable index for predicting soil erosion risk (Mikhailova *et al*., 1997). Accurate R-factor computation is especially valuable in regions lacking detailed precipitation records. In such scenarios, satellite-derived monthly precipitation data can be utilized to calculate average annual erosivity (Pandey & Gautam, 2015). These methodologies emphasize the importance of estimating rainfall erosivity, particularly in data-scarce areas, to effectively assess and manage soil erosion risks using precipitation erosivity metrics and satellite-based precipitation sources.

Soil Erodibility (K-Factor)

The K-factor, a key parameter in the RUSLE model, measures the soil's resistance to erosion caused by raindrop impact and concentrated surface flow (Veith *et al*., 2017). It represents soil erodibility and is used to assess sediment detachment and distribution across a landscape (Bayramin *et al*., 2007). The K-factor quantifies erosion potential by analyzing soil properties such as texture, organic matter content, and water retention. This allows for evaluating how changes in ecosystems or land management practices can mitigate erosion risks. To tailor the K-factor to specific soils and sites, several modified algorithms have been developed, enhancing its application across diverse environmental contexts (Rodrigo-Comino *et al*., 2020).

Slope Length and Steepness Factors (LS)

Slope length and steepness are crucial topographical factors influencing soil erosion, as they directly impact flow velocity (Ozsoy & Aksoy, 2015). Longer slopes experience increased erosion rates due to greater flow energy (Dudiak *et al.,* 2019). Steeper slopes, while gaining less water energy, lead to more significant soil displacement because of concentrated flow. In the RUSLE model, the LS factor is a dimensionless parameter that quantifies variations in soil erosion intensity based on slope length and steepness. This factor helps predict and manage erosion risks effectively by incorporating topographical characteristics (Gashaw *et al*., 2017). Studies emphasize the LS factor's importance in assessing erosion risk through slope dynamics, underscoring its role in soil conservation planning (Prasannakumar *et al*., 2012).

Land Cover Management Factor (C-Factor)

The C-factor in the RUSLE model assesses soil loss based on land cover, crops, and management practices, serving as a critical parameter for erosion prediction and control (Gashaw *et al*., 2017). It is a dimensionless value that reflects how specific land-use practices reduce soil erosion per unit area. This factor helps monitor and estimate soil loss associated with plant cover and residual matter, enabling evaluations of farmland management efficiency and guiding the development of mitigation strategies (Saha, 2018). Vegetation type, canopy structure, and land management practices significantly impact soil erosion rates, with the C-factor offering a framework to analyze and optimize these influences (Zhao *et al*., 2012).

Support Practice Factor (P-Factor)

The P-factor in the RUSLE model quantifies the effectiveness of soil conservation practices in mitigating erosion. It is calculated as the ratio of soil loss under a specific conservation practice to the soil loss observed from conventional up-and-down slope cultivation (Renard *et al*., 1997). This factor provides valuable insights into the efficiency of various soil management strategies, aiding in the development of targeted erosion control measures.

Table 1: Data for Estimation of soil erosion by RUSLE model

Factor	Description	Data Source	Calculation Method
R-factor	Rainfall and runoff erosivity factor measuring the erosive power of rainfall.	CHIRPS precipitation data	Total rainfall multiplied by 0.363, with 79 added to convert to an erosivity factor.
K-factor	Soil erodibility factor representing soil's susceptibility to erosion.	Regional soil dataset	Derived based on soil properties from the dataset.
LS-factor	Topographic factor accounting for slope length and steepness effects.	DEM data	Calculated from slope percent obtained from DEM data.
C-factor	Crop management factor indicating the impact of vegetation and management practices on erosion.	Sentinel-2 NDVI data	Estimated using NDVI derived from Sentinel-2 imagery.
P-factor	Support practice factor assessing the efficiency of soil conservation practices.	MODIS land-use and land-cover dataset, slope data	Derived using land-use/land-cover information and slope percent.

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 Bay state. The R-factor will ascertain the erosive force of rain and is calculated as follows:

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

This R-factor has applied to the RUSLE model mentioned by Panagos *et al*., (2017). The R-factor map of Bay regionis depicted in Figure 3. For the state the R-factor ranged from 359.92 to 616.2867. Hence, these values showed the potential rate of soil-loss to rainfall driven erosion in the Bay state. Higher the R-factor value, higher is the susceptibility of the area to soil erosion by rainfall.

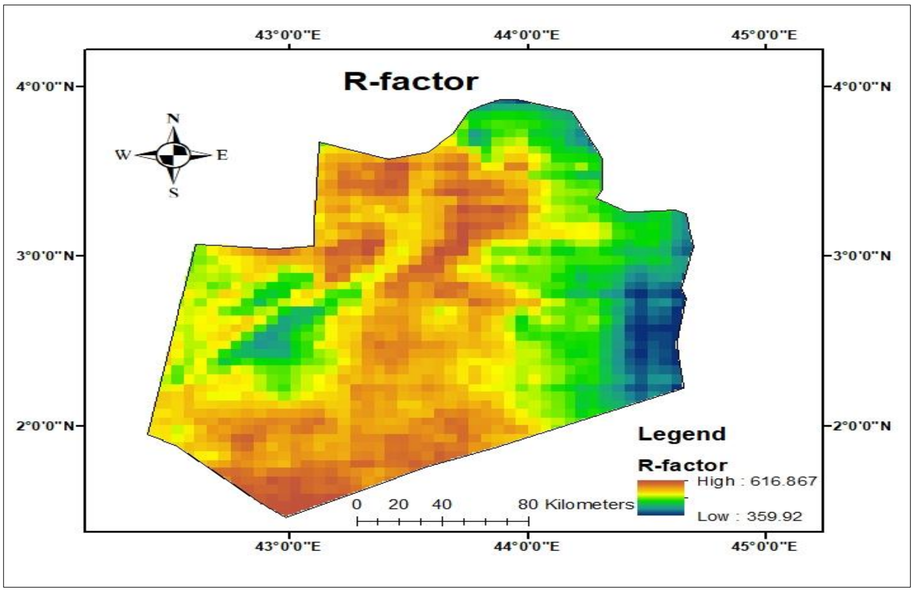

Figure 3: Rainfall erosivity (R-factor) map of Bay state

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, 0.027, 0.03, 0.04 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 Bay regionis given in Figure 4.

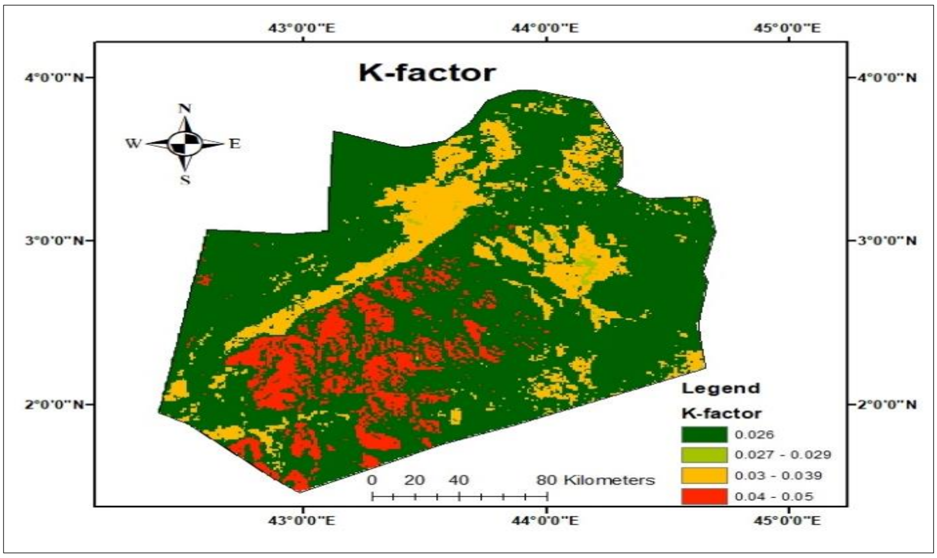

Figure 4: Soil erodibility (K-factor) map of Bay state

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:

Slope (%) = tan (slope in degrees) × 100.

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

LS = (Slope 0.53 + Slope^2 0.076 + 0.76) × √ (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, (Slope × 0.53 + Slope^2 × 0.076 + 0.76) refers to the effect of slope on erosion, including both linear and quadratic effects of slope, whereas √(500/100) represents the interference of the slope length. The square root in this function also represents a nonlinear relationship. Figure 5 shows the steepness of the landscape slopes of the different parts of the study area, which varies from 0 (flat area) to 11.2905 (extremely steep area).

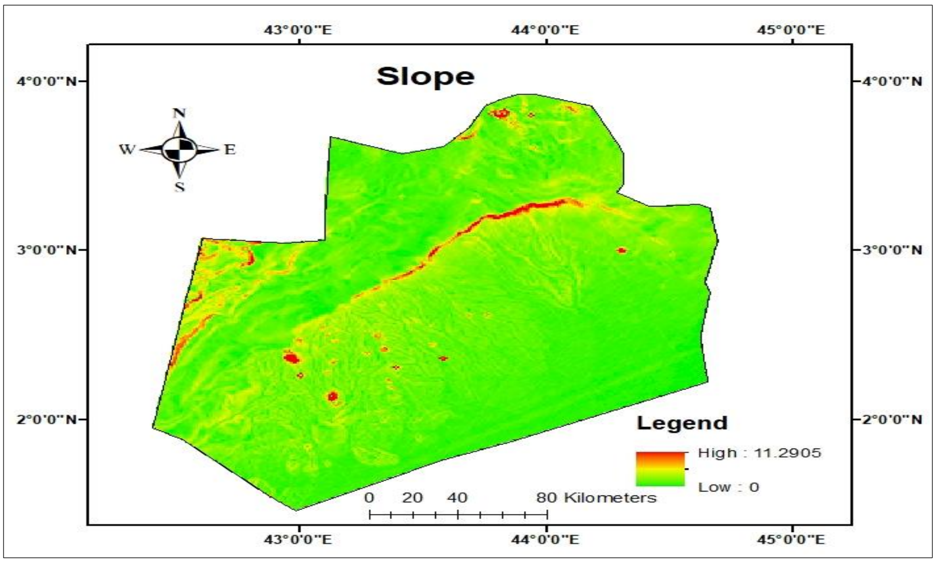

Figure 5: Slope map of Bay state

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 36.7433 (high erosion potential). The map of the LS factor of Bay regionis given in Figure 6.

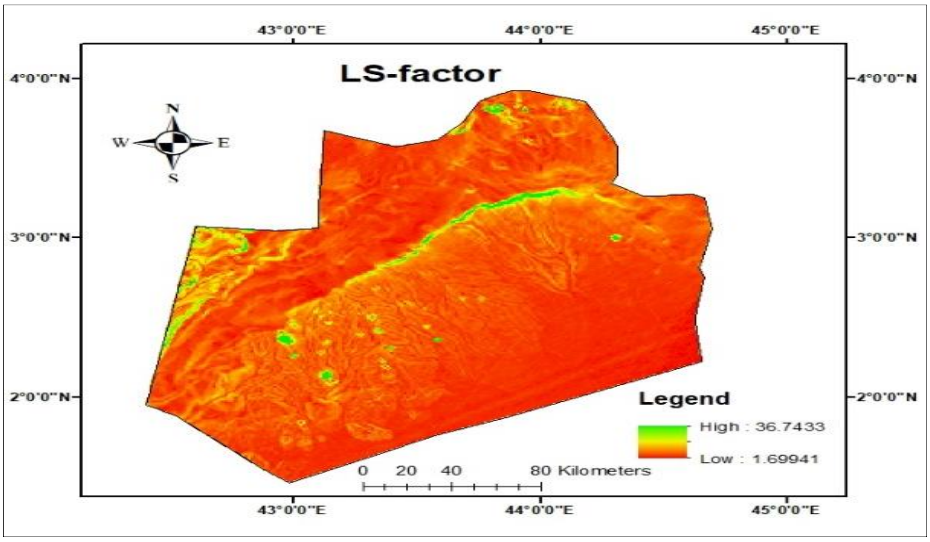

Figure 6: LS factor map of Bay state

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 Bay regionwas used to find the median value, and the values of NDVI ranged from 0.02 to 0.2. 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 Bay regionis given in Figure 7.

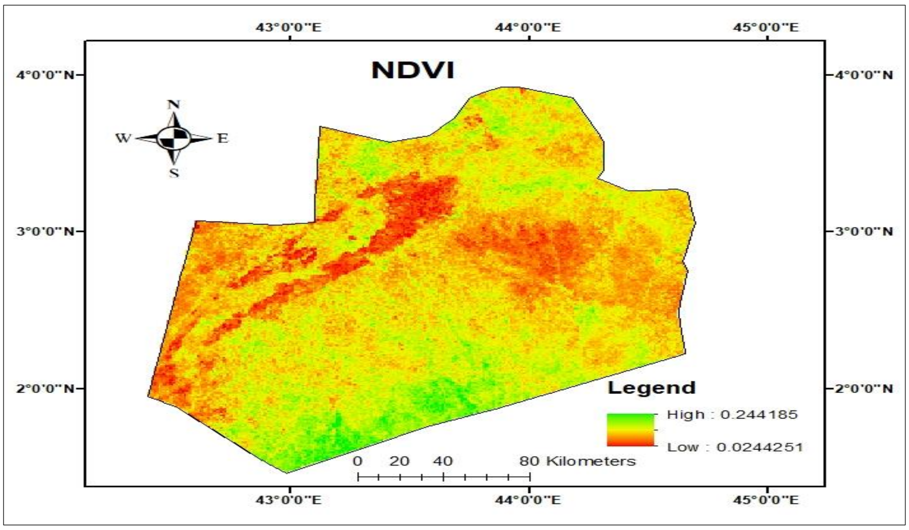

Figure 7: NDVI map of Bay state

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. Figure 8 represents the C-factor map of the study area. The values of 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.

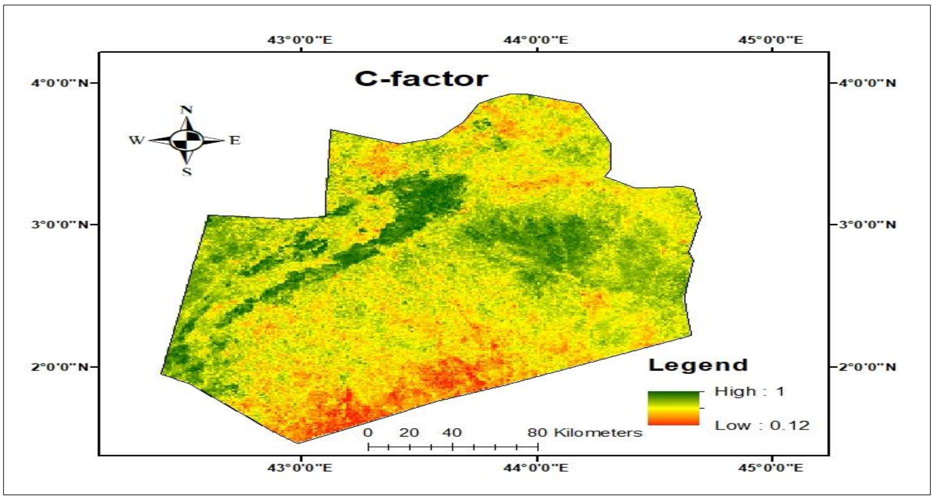

Figure 8: C-factor map of Bay state

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 which 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 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 (Figure 9) range from 0.5 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.

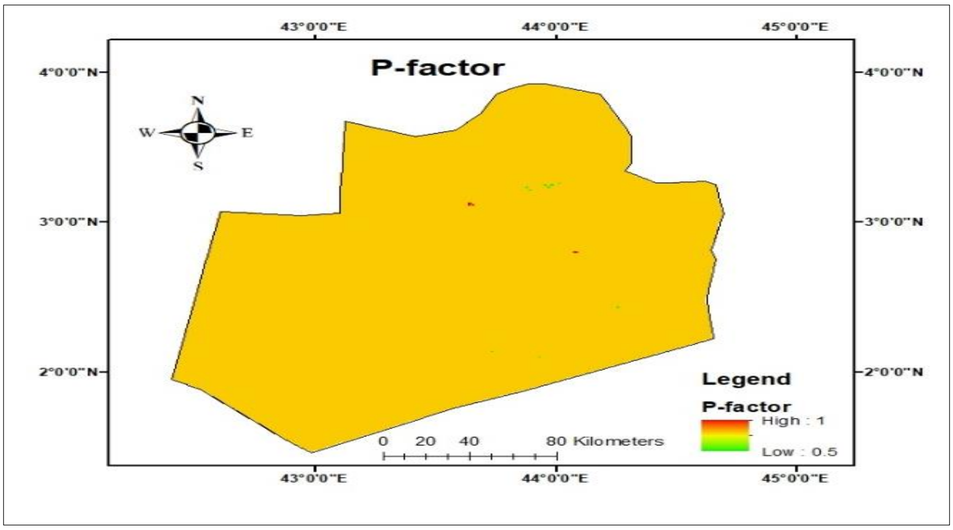

Figure 9: P-factor map of Bay state

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 2.

Table 2: Mean Values of the RUSLE Model

Parameters	Mean R Factor	Mean K Factor	Mean LS Factor	Mean C Factor	Mean P Factor	Mean Soil Loss
Mean Values	520.34	0.03	2.35	0.58	0.8	17.65

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 figure10 and depicted in Figure 11.

Distribution of Soil Loss Classes Along with Their Respective Areas

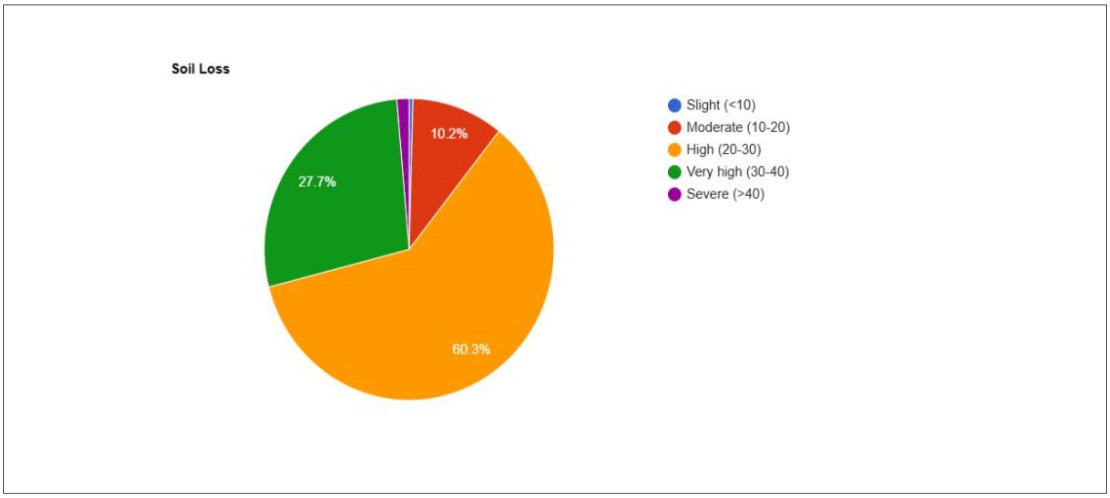

Figure 10: Distribution of Soil Loss Classes and Their Areas in Bay State

The chart above provides a detailed breakdown of the distribution of areas across different soil loss classes. It categorizes the severity of soil loss, highlighting the extent and vulnerability of various regions within Bay State. This visual representation complements the soil loss map, offering quantitative insights that aid in understanding the spatial patterns observed in the map.

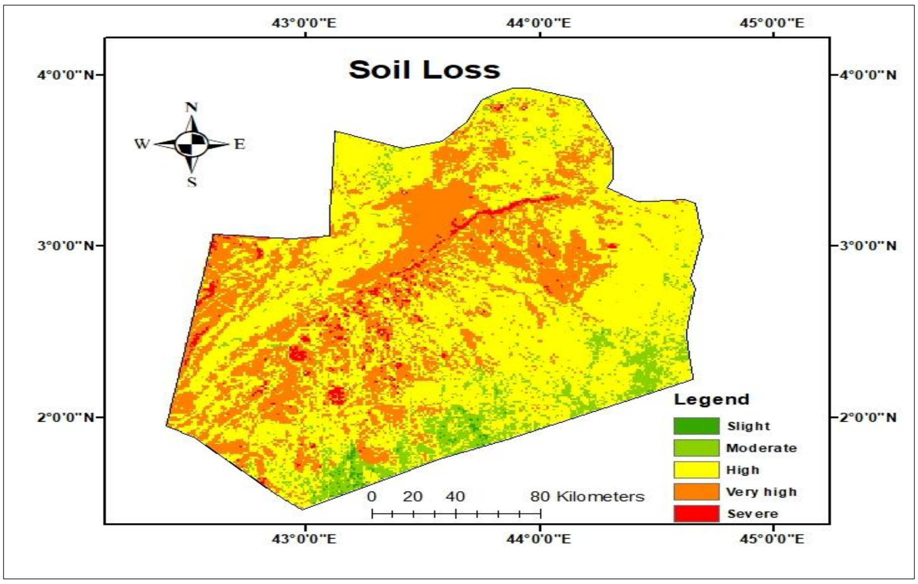

Figure 11: Soil loss map of Bay state

DISCUSSION

The estimation of the R-factor, starting from 359.92.to a high of 616.867 (Figure 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 (Figure 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 (Figure 5 and Figure 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 (Moses 2017). The NDVI evaluation (Figure 7) and derived C-factor (Figure 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 0.5 to 1 (Figure 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 Bay region (Figure 11). The categorization of soil loss into "Slight," "Moderate," "High," "very high," and "Severe" 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 Bay region (Nur *et al*., 2024) According to Nur *et al*., 2024, Spatial Assessment of Erosivity and Arid Conditions in Somalia Using the CORINE Model, integrating soil erodibility, erosivity, slope, and land cover data. Climatic indices like the Modified Fournier Index (MFI) and Bagnouls-Gaussen Index (BGI) were calculated the study found that 99.17% of the study area is at moderate erosion risk, with steep slopes increasing runoff. Low erosivity risk, covering 32.14% of the area, was mainly in the northern regions. Sparse vegetation and steep terrains were identified as key risk factors. These findings provide valuable insights for soil conservation efforts, particularly in arid environments (Nur *et al*., 2024).

CONCLUSION

An extensive study on soil erosion in the Bay regionoffers 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 Bay 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 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.

REFERENCES

- Abidin, R.Z., Mahamud, M.A., Yusof, M.F., Zakaria, N.A. and Arumugam, M.A.R.M.A., 2021. Determination of cover management and soil loss risk mapping by sub-districts and river catchments of Cameron Highlands Malaysia. *Land,* 10(11), pp.1181. DOI: 10.3390/land10111181
- Afriyie, E., Verdoodt, A. and Mouazen, A.M., 2020. Estimation of aggregate stability of some soils in the loam belt of Belgium using mid-infrared spectroscopy. *Science of The Total Environment*, 744, pp.140727. DOI: https://doi.org/10.1016/j.scitotenv.2020.140727
- Ailincăi, C., Jitareanu, G., Bucur, D. and Mercuş, A., 2011. Evolution of some chemical properties of soil under influence of soil erosion and different cropping systems. *Cercetari Agronomic in Moldova,* 44(4). DOI: 10.2478/v10298-012-0044-3
- Alexiou, S., Efthimiou, N., Karamesouti, M., Papanikolaou, I., Psomiadis, E. and Charizopoulos, N., 2023. Measuring annual sedimentation through high accuracy UAV-Photogrammetry data and comparison with RUSLE and PESERA Erosion Models. *Remote Sensing,* 15(5), pp.1339. DOI: 10.3390/rs15051339

- Amsalu, T. and Mengaw, A., 2014. GIS based soil loss estimation using RUSLE model: The case of Jabi Tehinan Woreda, ANRS, Ethiopia. *Natural Resources,* 5(16), pp.616-626.
- Angima, SD., Stott, D.E., O'Neill, M.K., Ong, C.K. and Weesies, G.A., 2003. Soil erosion prediction using RUSLE for central Kenyan highland conditions. *Agriculture, Ecosystems & Environment,* 97(1-3), pp.295-308.
- Barrow, I.H. (2020). Inter-Clan Conflicts in Somalia: When Peace Happen (Case Study Baidoa District, Bay Region). *International Journal of Human Resource Studies*.
- Bayramin, İ., Basaran, M., Erpul, G. and Canga, M.R., 2007, September 5. Assessing the Effects of Land Use Changes on Soil Sensitivity to Erosion in a Highland Ecosystem of Semi-Arid Turkey. https://scite.ai/reports/10.1007/s10661-007-9864-2
- Birhan, M. (2013). Livestock Resource Potential and Constraints in Somali Regional State, Ethiop
- Bou-imajjane, L. and Belfoul, M.A., 2020. Soil loss assessment in Western High Atlas of Morocco: Beni mohand watershed study case. *Applied and Environmental Soil Science,* 143, pp.1-15. DOI: 10.1155/2020/6384176
- Chala, H.M., 2019. A geographic information system-based soil erosion assessment for conservation planning at West Hararghe, Eastern Ethiopia. *Civil Engineering and Environmental Systems,* 11(2), pp.19. DOI: 10.7176/cer/11-2-02
- Chapman, S., Birch, C.E., Galdos, M.V. and Bellerby, T.J., 2021. Assessing the impact of climate change on soil erosion in East Africa using a convection-permitting climate model. *Environmental Research Letters,* 16(9), pp.094036.
- Chen, X., Liu, X., Peng, W., Dong, F., Huang, Z. and Wang, R., 2017. Non-Point Source Nitrogen and Phosphorus Assessment and Management Plan with an Improved Method in Data-Poor Regions. *Water,* 10(1), pp.17. DOI: 10.3390/w10010017
- Cui, H., Wang, Z., Yan, H., Li, C., Jiang, X., Liu, G., Hu, Y., Yu, S. and Shi, Z., 2022. Production-based and consumption-based accounting of global cropland soil erosion. *Environmental Science & Technology,* 56(14), pp.10465-10473. DOI: 10.1021/acs.est.2c01855
- Dabney, S.M., Yoder, D.C., Vieira, D.A. and Bingner, R.L., 2012. Enhancing RUSLE to include runoff-driven phenomena. *Hydrological Processes,* 26(6), pp.910-922.
- Desmet, P.J. and Govers, G., 1996. A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. *Journal of Soil and Water Conservation,* 51(5), pp.427-433.
- Dhaloiya, A., Nain, A.S., Sharma, M.P. and Singh, A., 2021. Prioritization of watershed using Remote Sensing and Geographic Information System. *Sustainability,* 13(16), pp.9456. DOI: https://doi.org/10.3390/su13169456
- Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F. and Bargellini, P., 2012. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment,* 120, pp.25–36. DOI: https://doi.org/10.1016/j.rse.2011.11.026
- Dudiak, N.V., Pichura, V.I., Potravka, L. and Stratichuk, N.V., 2019, September 1. Geomodelling of Destruction of Soils of Ukrainian Steppe Due to Water Erosion. https://scite.ai/reports/10.12911/22998993/110789
- Fenta, A.A., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Yasuda, H., Ebabu, K. and Kawai, T., 2020. Land susceptibility to water and wind erosion risks in the East Africa region. *Science of the Total Environment,* 703, pp.134807.
- Gaonkar, V.G., Nadaf, F.M. and Kapale, V., 2024. Mapping and Quantifying Integrated Land Degradation Status of Goa Using Geostatistical Approach and Remote Sensing Data. *Nature Environment & Pollution Technology*, 23(1). DOI: 10.46488/NEPT.2024.v23i01.025Abidin, R Z., Mahamud, M A., Yusof, M F., Zakaria, N A., & Arumugam, M. A. R. M. A. (2021). Determination of Cover Management and Soil Loss Risk Mapping by Sub-Districts and River Catchments of Cameron Highlands Malaysia.
- Gashaw, T., Tulu, T. and Argaw, M., 2017, January 6. Erosion Risk Assessment for Prioritization of Conservation Measures in Geleda Watershed, Blue Nile Basin, Ethiopia. https://scite.ai/reports/10.1186/s40068-016-0078-x
- Housseyn, B., Nekkache, G.A., Kamel, K., Hamza, B. and Saleh-Eddine, T., 2021. Estimation of soil losses using RUSLE model and GIS tools: Case study of the Mellah catchment, Northeast of Algeria. *Romanian Journal of Civil Engineering,* 12 (3), pp.266-289. DOI: 10.37789/rjce.2021.12.3.2
- Hua, T., Zhao, W., Liu, Y. and Liu, Y., 2019. Influencing factors and their interactions of water erosion based on yearly and monthly scale analysis: A case study in the Yellow River basin of China. *Natural Hazards and Earth System Sciences Discussions.* DOI: 10.5194/nhess-2019-122
- Ibrahim, A. A., Nur, A. H., Farah, F. A., Ahmed, S. M. & Warsame, A. A. (2025). Impacts of Climate Change on FoodSecurity in Somalia: Challenges and Adaptation Strategies. African Journal of Climate Change and Resource Sustainability,4(1), 130-147. https://doi.org/10.37284/ajccrs.4.1.2765
- Karamage, F., Zhang, C., Ndayisaba, F., Shao, H., Kayiranga, A., Fang, X., Nahayo, L., Nyesheja, E.M. and Tian, G., 2016. Extent of cropland and related soil erosion risk in Rwanda. *Sustainability,* 8(7), pp.609. DOI: https://doi.org/10.3390/su8070609

- Kogo, B.K., Kumar, L. and Koech, R., 2020. Impact of land use/cover changes on soil erosion in western Kenya. *Sustainability,* 12(22), pp.9740.
- Laflen, J.M. and Moldenhauer, W.C., 2003. Pioneering soil erosion prediction: The USLE story. *International Soil and Water Conservation Research,* 34(2). DOI: 10.1016/S2095-6339(15)30034-4
- Lense, G.H.E., Moreira, R.S., Bócoli, F.A., Avanzi, J.C., Teodoro, A.E.D.M. and Mincato, R.L., 2020. Estimation of sediments produced in a subbasin using the Normalized Difference Vegetation Index. *Ciência e Agrotecnologia,* 44(4). DOI: 10.1590/1413-7054202044031419
- Li, Z., Guo, R., Li, M., Chen, Y. and Zhang, Y., 2020. Characterizing spatiotemporal vegetation dynamics in the Greater Mekong Subregion with NDVI and EVI time series. *Journal of Forestry Research,* 31, pp.1347–1362.
- Mc Cool, D.K., Brown L.C., Foster G.R., Mutchler C.K. and Meyer, L.D., 1987. Revised slope steepness factor for universal soil loss equation Transactions of American Society of Agricultural Engineers. *Transactions of the ASAE,* 30(5), pp.1387-1396. DOI: 10.13031/2013.30576
- Mikhailova, E.A., Bryant, R.B., Schwager, S.J. and Smith, S.D., 1997. Predicting rainfall erosivity in Honduras. *Soil Science Society of American Journal,* 61(1), pp.273-279. DOI: https://doi.org/10.2136/sssaj1997.03615995006100010039x
- Moses, A.N., 2017. GIS-RUSLE interphase modelling of soil erosion hazard and estimation of sediment yield for River Nzoia Basin in Kenya. *Journal of Remote Sensing and GIS,* 6(4).
- Nguyen, M.H., 2011. Application USLE and GIS Tool to Predict Soil Erosion Potential and Proposal Land Cover Solutions to Reduce Soil Loss in Tay Nguyen.
- Nur, A. H., & Mohamed, A. A. (2024). Spatial assessment of soil erosion and aridity in Somalia using the CORINE model. Asian Soil Research Journal, 8(4), 10-9734.
- Nur, A. H., Faruq Hasan, M., Sarmin, S., Shahin, A., Mohamed, A. A., & Ahmed, A. H. (2025). Geospatial Assessment of Soil Erosion Using Revised Universal Soil Loss Equation in Hirshabelle State of Somalia. *Nature Environment & Pollution Technology*, *24*.
- Nur, A. H., Ibrahim, A. A., Warsame, A. A., & Farah, A. H. (2024). Estimation of soil erosion and risk assessment in Somalia. International Journal of Agricultural Research, Innovation and Technology (IJARIT), 14(2), 111-121.
- Nur, A.H., Ahmed, A.H., Mohamed, A.A., Hasan, M.F. and Sarmin, S., 2024. Geospatial assessment of Aridity and Erosivity Indices in Northwest Somalia using the CORINE Model. *Journal of Environmental and Science Education,* 4(1), pp.1-11
- Omuto, C., Balint, Z. and Alım, M., 2011. A framework for national assessment of land degradation in the drylands: A case study of Somalia. *Land Degradation and Development,* 25(2). DOI: 10.1002/ldr.1151
- Orchard, P.J., 2021. Enabling Multi-Site Stormwater Environmental Compliance Approvals in Ontario, Canada.
- Oshunsanya, S.O. and Nwosu, N.J., 2017. Suitability of Universal Soil Loss Erodibility, Inter-rill and Rill Erodibility Models for Selected Tropical Soils. *Agricultura Tropica Et Subtropica, 50(4), pp.* DOI:191-198 DOI: 10.1515/ats-2017-0020
- Ozsoy, G. and Aksoy, E., 2015. June 10. Estimation of Soil Erosion Risk within an Important Agricultural Sub-Watershed in Bursa, Turkey, in relation to rapid urbanization. https://scite.ai/reports/10.1007/s10661-015-4653-9
- Pahlevan, N., Sarkar, S., Franz, B.A., Balasubramanian, S.V. and He, J., 2022. Cross-calibration of S-NPP VIIRS and Sentinel-2A/2B MSI for improved terrestrial monitoring. Remote Sensing, 14(4), pp.681.
- Panagos, P., Borrelli, P. and Meusburger, K., 2017. Estimating the RUSLE Equation Rainfall Factor in the Calculations of Global Soil Erosion. Geophysical Research Abstracts, 19.
- Pandey, A. and Gautam, A.K., (2015, October 1). Soil Erosion Modeling using satellite rainfall estimates. *Journal of Water Resource and Hydraulic Engineering,* 4(4), pp.318-325. DOI: 10.5963/JWRHE0404002
- Patil, M., Patel, R. and Saha, A., 2021. Sediment yield and soil loss estimation using GIS based Soil Erosion Model: A case study in the MAN Catchment, Madhya Pradesh, India. *Environmental Sciences Proceedings,* 8(1), pp.26. DOI: 10.3390/ecas2021-10348
- Prasannakumar, V., Vijith, H., Abinod, S. and Geetha, N., 2012. Estimation of soil erosion risk within a small mountainous sub-watershed in Kerala, India, using Revised Universal Soil Loss Equation (RUSLE) and geo-information technology. *Geoscience Frontiers,* 3(2), pp.209–215. DOI: 10.1016/j.gsf.2011.11.003
- Puente, C., Olague, G., Trabucchi, M., Arjona-Villicaña, P.D. and Soubervielle-Montalvo, C., 2019. Synthesis of Vegetation Indices using genetic programming for soil erosion estimation. *Remote Sensing,* 11(2), pp.156. DOI: https://doi.org/10.3390/rs11020156
- Reiche, J., Hamunyela, E., Verbesselt, J., Hoekman, D. and Herold, M., 2018. Improving near-real time deforestation monitoring in tropical dry forests by combining dense Sentinel-1-time series with Landsat and ALOS-2 PALSAR-2. *Remote Sensing of Environment,* 204, pp.147–161.
- Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K. and Yoder, D.C., 1996. Predicting soil erosion by

water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). *Environmental Science.* DOI: https://api.semanticscholar.org/CorpusID:128575343

- Rocha, G.C.D. and Sparovek, G., 2021. Scientific and Technical Knowledge of Sugarcane Cover-Management USLE/RUSLE Factor.
- Rodrigo-Comino, J., Senciales-González, J.M. and Ruiz-Sinoga, J.D., 2020, March 16. The effect of hydrology on soil erosion. *Water,* 12(3), pp.839. DOI: 10.3390/w12030839
- Saha, A., 2018, August 8. GIS Based Soil Erosion Estimation Using Rusle Model: A Case Study of Upper Kangsabati Watershed, West Bengal, India. https://scite.ai/reports/10.19080/ijesnr.2018.13.555871
- Sarmin, S., Hasan, M.F., Hanif, M.A., Nur, A.H. and Shahin, A., 2023. *From Pixels to Policies: Remote Sensing for Compliance with Agriculture 4.0.* In: GRISS An Edited Book (Volume-3), Edited by S.P. Singh. Astha Foundation, Meerut, India.
- Stathopoulos, N., Lykoudi, E., Vasileiou, E., Rozos, D. and Dimitrakopoulos, D., 2017. Erosion uulnerability assessment of Sperchios river basin, in East Central Greece— A GIS based analysis. Open *Journal of Geology,* 7(05), 621-6467. DOI: 10.4236/ojg.2017.75043
- Tamene, L., S., Park, R., Dikau, and Vlek, P.L.G., 2006. Analysis of factors determining sediment yield variability in the highlands of Ethiopia. *Geomorphology,* 76(1), pp.76-91. DOI: 10.1016/j.geomorph.2005.10.007
- Tegegne, M.A., Zewudu, Y. and Fentahun, T., 2022. Erosion Source Area Identification Using Rusle and Multi-Criteria Decision Analysis, Acase of Andassa Watershed, Upper Blue Nile Basin. DOI: 10.21203/rs.3.rs-1718698/v1
- Trinh, C.T., 2015. *Soil Erosion in Vietnam (The Case of Buon Yong catchment) Universal Soil Loss Equation (RUSLE).* Scholars Press.
- Veith, T.L., Goslee, S.C., Beegle, D.B., Weld, J. and Kleinman, P.J.A., 2017. November 1. Analyzing Within-County Hydrogeomorphological Characteristics as a Precursor to Phosphorus Index Modifications. https://scite.ai/reports/10.2134/jeq2016.10.0416
- Vezina, K., Bonn F. and Pham V.C., 2006. Agricultural land-use patterns and soil erosion vulnerability of watershed units in Vietnam's northern highlands. *Landscape Ecology,* 21(8), pp.1311-1325. DOI: 10.1007/s10980-006-0023-x
- Vrieling, A., Rodrigues, S.C. and Sterk, G., 2005. Evaluating erosion from space : A case study near Uberlândia. Sociedade & natureza, *In Sociedade & Natureza,* Special issue : International Symposium on Land Degradation and Desertification, pp. 683-696.
- Wagari, M. and Tamiru, H., 2021. January 1. RUSLE model based annual soil Loss Quantification for Soil Erosion Protection: A Case of Fincha Catchment, Ethiopia. https://scite.ai/reports/10.1177/11786221211046234
- Wang, H. and Zhao, H., 2020. Dynamic Changes of Soil Erosion in the Taohe River Basin Using the RUSLE Model and Google Earth Engine. *Water,* 12(5), pp.1293. DOI: 10.3390/w12051293
- Wang, R., Zhang, S., Yang, J., Pu, L., Yang, C., Yu, L., Chang, L. and Bu, K., 2016. Integrated use of GCM, RS, and GIS for the assessment of hillslope and gully erosion in the Mushi river Sub-Catchment, Northeast China. *Sustainability,* 8, Pp.317. DOI: https://api.semanticscholar.org/CorpusID:14514293
- Wischmeier, W.H. and Smith, D.D., 1978. Predicting rainfall erosion losses: A guide to Conservation Planning World Association of Soil and Water Conservation, Beijing, China, p. 54
- Wischmeier, W.H. and Smith, D.D., 1978. *Predicting Rainfall Erosion Losses. A Guide to Conservation Planning.* The USDA Agricultural Handbook No. 537, Maryland.
- Wischmeier, W.H., 1976. Use and misuse of the universal soil loss equation. *Journal of Soil and Water Conservation,* 31(1), 5-9.
- Yan, X., Wu, L., Xie, J., Wang, Y., Wang, C. and Ling, B., 2022. Dynamic Changes and Precision Governance of Soil Erosion in Chengde City Using the GIS Techniques and RUSLE Model. *Nature Environment & Pollution Technology*, 21(3). DOI: 10.46488/NEPT.2022.v21i03.009
- Yebra, M., Chuvieco, E. and Riaño, D., 2008. Estimation of live fuel moisture content from MODIS images for fire risk assessment. *Agricultural and Forest Meteorology,* 148(4), pp.523-536.
- Yesuph, Y.S., Endalamaw, N.T., Sinshaw, B.G. and Ayana, E.K., 2021. Modeling soil erosion using RUSLE and GIS at watershed level in the upper Beles, Ethiopia. *Environmental Challenges,* 3, pp.100039.
- Zhang, J., Xiao, X., Wu, X. and Zhou, S., 2016. A global moderate resolution dataset of gross primary production of vegetation for 2000–2016. *Scientific Data,* 5, pp.180165.
- Zhao, W., Fu, B. and Chen, L.D., 2012. August 16. A Comparison between Soil Loss Evaluation Index and the C-factor of RUSLE: A Case Study in the Loess Plateau of China. https://scite.ai/reports/10.5194/hess-16-2739-2012
- Zhou, Q., Yang, S., Zhao, C., Cai, M. and Luo, Y., 2014. A soil erosion assessment of the upper Mekong river in Yunnan Province, China. *Mountain Research and Development,* 34(1), pp.36-47. DOI: 10.1659/MRD-JOURNAL-D-13-00027.1

Cite This Article: Abdiaziz Hassan Nur, Jamal Abdikarim Mohamed, Abdourahaman Sahal Hussein, Nasreen Sultana Orchy (2025). GIS-Based on Assessment of Soil Erosion in Bay Region of Somalia. *East African Scholars J Agri Life Sci, 8*(6), 122-134.