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Integrating Multi-Criteria Analysis and GIS for Assessing Land Degradation Vulnerability in Choke Mountain, Upper Blue Nile River

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Abstract: *Evaluating land degradation is crucial for identifying vulnerable areas and developing sustainable landscape management strategies. In this study, Geographic Information System (GIS) combined with Multi-Criteria Analysis (MCA) was used to map and assess land degradation in Choke Mountain watershed, Upper Blue Nile. This involved a comprehensive evaluation of physical, chemical, and biological indicators of land degradation. Each indicator was standardized and weighted through pairwise comparisons and the Analytical Hierarchy Process (AHP). The analysis revealed that approximately 50.64% of the watershed faces a high to extremely high risk of soil loss, with an average soil loss rate of 44 t ha^{-1} yr^{-1}. Furthermore, over half of the watershed experienced moderate to high biological degradation, characterized by low vegetation cover and decreased soil organic matter. Overall, 70.7% of the region showed moderate physical land degradation. In terms of biological degradation, 37.4% of the watershed was classified as low, and 55.5% as moderate. Regarding chemical degradation, most of the area (55.6%) had a soil pH between 6.7 and 7.3, which is considered neutral. The combined spatial MCA of biological, chemical, and physical indicators indicated that 1.2%, 25.5%, 37.15%, and 36.15% of the watershed fell into very low, low, moderate, and high degradation categories, respectively. The study concludes that high biological deterioration and soil erosion are the most significant indicators of land degradation in Choke Mountain watershed. It recommends integrated land management approaches to reduce land degradation, improve soil organic matter, and enhance vegetation cover.*

Keywords: Land Degradation; Soil Erosion; GIS; MCA; Choke Mountain, *Upper Blue Nile*

I. INTRODUCTION

Land is a natural capital serves as both the foundation for terrestrial ecosystem functions and a critical form of natural capital essential for human survival(Le et al., 2016; Xie et al., 2020). Healthy land is often the primary source of livelihood for rural populations in developing countries(Le et al., 2016). However, negligent and unsustainable land use leads to severe landscape degradation (Nkonya et al., 2015). Land degradation is a slow-moving environmental issue caused by both natural and human activities, with impacts that accumulate over time(Bai et al., 2008).It refers to the gradual loss of ecosystem productivity and function resulting from disturbances that the land cannot recover from quickly (Bai et al., 2008). Processes such as deforestation, biodiversity loss, and soil degradation reduce the ability of land resources to provide essential ecosystem services(Ewunetu et al., 2021a). Land degradation is brought on by a variety of types. It includes, among other types of land degradation, biological degradation (such as loss of biodiversity), soil degradation (such as soil erosion), and water scarcity(Berry et al., 2003; Ewunetu et al., 2021a).

Globally, land degradation has severely impacted about 24% of the Earth's surface (UNCCD, 2015) in general, and nearly 20% of cropland, 10% of grassland, and 30% of forest land degraded(Nkonya & Mirzabaev, 2016). Africa is one of the most severely affected regions by land degradation coupled with climate change (Ngetich et al., 2014). According to UNCCD (2011), approximately 30% of its productive land is degraded, posing significant challenges for agriculture and food security. In Ethiopia, land deterioration is a chronic and severe problem on the environment (Bantider, 2023). Over 85% ofthe country's landmass is degraded to varying degrees(Gebreselassie, 2016), primarily due to factors such as population pressure, poverty, rugged topography, climate change, reliance on biomass for fuel, and poor land management practices (Reed et al., 2015).

In Ethiopia, deforestation remains a significant driver of land degradation, contributing to local soil erosion, biodiversity loss, and changes in hydrology(Reusing et al., 2017). At the beginning of the 20th century, forest biomass covered over 40% of the land area(Gebru, 2016), but this percentage has now decreased to 12%(Gashaw, Tulu, Argaw, et al., 2017). In Ethiopian highlands, soil erosion caused by water is the most prevalent form of land degradation. Notably, the northern highlands have experienced significant topsoil loss, estimated at 45 t ha^{-1} yr^{-1} (Tamene et al., 2022). In the northwest, the rate is approximately 33.7t ha^{-1} yr^{-1}, (Olika & Iticha, 2019), while the Upper Blue Nile Basin of Ethiopia loses about 27.5t $ha^{-1}yr^{-1}$ (Molla & Sisheber, 2016). In addition, soil acidity has become a major concern in the region in recent years (Yirga et al., 2019).The Choke Mountain, the study area, is located in theNorthwestern Ethiopian highlands and was once recognized as having a high potential for agricultural production. However, the area's land resources have been steadily deteriorating, and the ecosystem productivity has been dropping and fragmented at a startling rate.

Continuous updates to land degradation vulnerability information is crucial because the process is dynamic and influenced by ongoing natural and human activities (Agyemang & Carver, 2014). Therefore, quantitative mapping of land erosion vulnerability is essential for stakeholders to prioritize at-risk areas for intervention(Ewunetu et al., 2021b; Malav et al., 2022). In Ethiopia, previous studies have examined land degradation using single indicators such as soil erosion or deforestation(Eshetu & Abegaz, 2024; Molla & Sisheber, 2016); however, a holistic, multi-criteria approach that incorporates physical, biological, and chemical degradation is lacking (Ewunetu et al., 2021). This study addresses this gap by integrating MCA and GIS through AHP to develop a comprehensive land degradation index for the Choke Mountain. Such studies are scarce in Ethiopia, particularly in the Choke mountain(Haregeweyn et al., 2017). This area is severely deteriorated, prone to climate variability, and has erratic rainfall. Thus, this research fills a critical gap in existing literature and provides compelling evidence that could lead to contribution to regional environmental policy and planning, in land and water management, ecosystem services assessment and environmental management planning and policy making issues.

This study adopts an innovative approach to quantify degraded land and estimate topsoil erosion rates by integrating RUSLE, MCA, and GIS within an AHP framework. This method involves analyzing multiple factors using spatial MCA combined with GIS and AHP (Ren et al., 2022).The spatial MCA technique is commonly used to address problems involving multiple complex variables by dividing them into sections, solving each one, and then integrating the results to achieve a comprehensive outcome (Ewunetu et al., 2021b; Malav et al., 2022; Ren et al., 2022).Consequently, the primary aim of this research was to assess the land degradation status on Choke Mountain using spatial MCA and GIS. Specifically, the objectives were (1) to estimate annual soil loss, (2) to map the spatial distribution of key biological, physical, and chemical indicators of land degradation, and (3) to produce a composite land degradation index map of the study area.

This study identifies severe land degradation areas in Choke Mountain. Thus, the study can provide insight for stockholders in applying best interventions in sustainable land management practices such as afforestation, reforestation, soil and water conservation measures, and sustainable agricultural practices, which can help to mitigate land degradation in this particular area. The study also provides a useful framework for future agriculture and land management research.

II. METHODS AND MATERIALS

2.1. Description of the Study Area

The Choke Mountain watershed is located in the upper Blue Nile region of northwestern Ethiopia highland, between 38.2°E and 39.6°E longitudes and 10.8°N and 11.9°N latitudes. It serves as a major tributary to the Blue Nile (Abay) River and covers a land area of approximately 1,994,620 hectare. The elevation within the watershed ranges from 710 to 4,038 meters above sea level (Fig.1). The dominant agro-ecological zones include tepid to cool moist mid-highlands and cold to very cold moist sub-Afro-alpine to Afro-alpine highlands (Simane et al., 2016). According to the Ethiopian National Meteorological Agency, the average maximum and minimum temperatures of the mountain range from 24.6–28.1°C and 11.0–14.5°C, respectively, with a mean annual temperature of 19.4°C (Simane et al., 2016). Rainfall in the watershed is closely associated with the annual migration of the Inter-Tropical Convergence Zone (ITCZ), with the majority of precipitation occurring during the summer months of June to September(Ewunetu et al., 2023).

Meteorological data from stations within and around the watershed indicate that the mean annual rainfall between 1986 and 2017 was 1,334.48 mm (Fig.1), with recorded minimum and maximum values of 810 mm and 1,815 mm, respectively (EMA, 2018). The dominant soil types in the watershed include Nitisols, Alisols, Cambisols, Leptosols, Vertisols, and Luvisols(Yilma & Awulachew, 2009). Geologically, the watershed is primarily composed of basalt formations, while the lowland areas are dominated by sandstone(Yilma & Awulachew, 2009).Natural forest cover in the area is sparse, limited mainly to riverbanks, hillsides, and small patches surrounding churchyards. In contrast, Eucalyptus globulus plantations are widely distributed, particularly in the highland areas, forming a dominant component of introduced tree species.

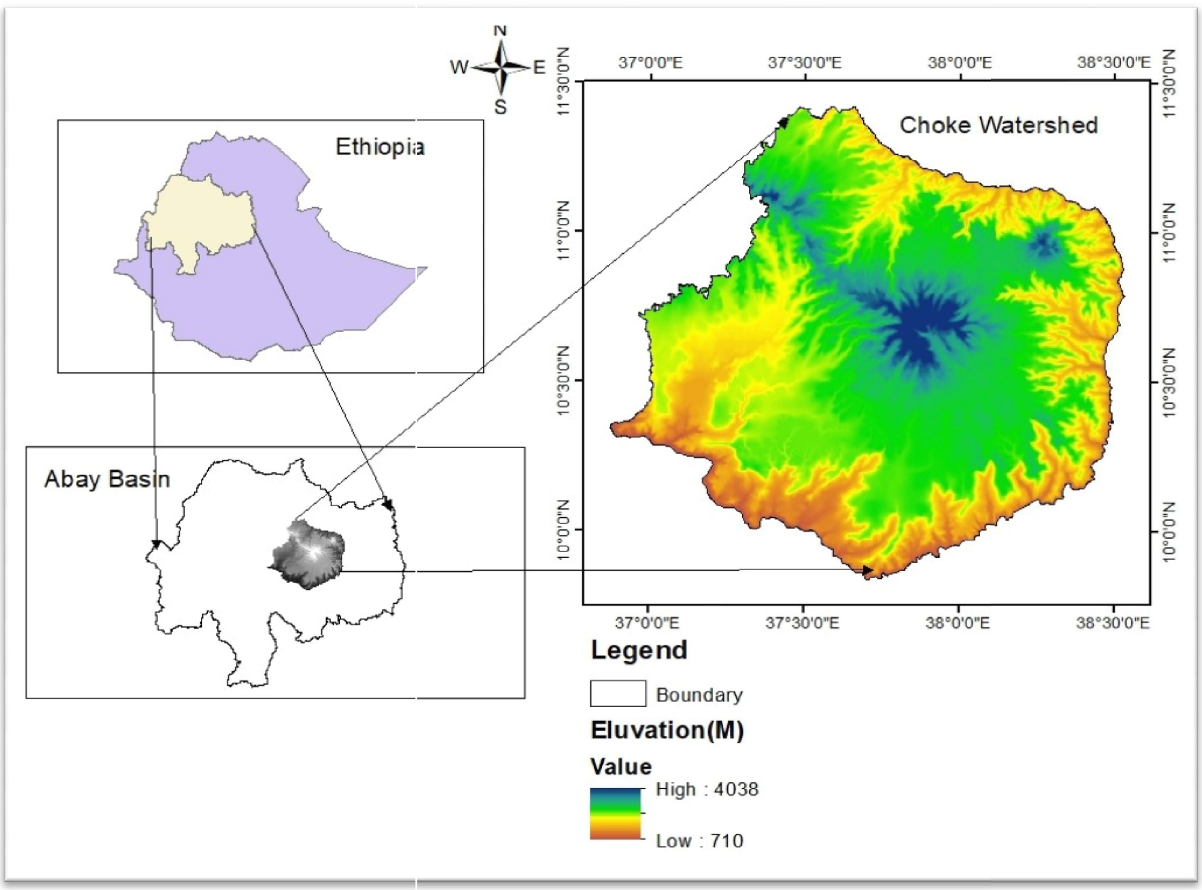

Fig.1: The location and topography of Choke Mountain watersheds

The livelihoods of the Choke Mountain population largely depend on rain-fed mixed crop-livestock agriculture, which is highly vulnerable to climatic variability. Livestock species commonly raised include cattle, oxen, sheep, and horses. A notable feature of agricultural practices in the region is the use of the traditional Ethiopian ard (maresha) plough, a simple ox-drawn wooden plough. While effective for breaking through hard, dry tropical clay soils, this tillage practice is associated with high rates of on-field soil erosion, especially on steep slopes, and often leads to the formation of a plough pan that reduces water infiltration.Additional factors such as overgrazing and deforestation have further aggravated soil erosion and fertility decline in the Choke Mountain watershed. The increasing demand for livestock feed and fuel-wood continues to exert pressure on the limited natural resources, intensifying the environmental challenges faced in the area.

2.2. Materialsand Methods

2.2.1. Nature and Data Sources

Landsat 8 Operational Land Imager (OLI) 2022 images were downloaded from the US Geological Survey (USGS) Earth Explorer (http://glovis.usgs.gov) for January, during the dry season, to obtain images with low cloud cover. ASTER Global Digital Elevation Model data were obtained from http://gdex.cr.usgs.gov/gdex/. Currently, satellite-based precipitation estimates have become an alternative source of sparse rainfall-gauge data for various hydrologic applications, especially in regions with limited data, like Africa, which lacks sufficient surface monitoring resources. Among others, Climate Hazards Group Infra-Red Precipitation with Station data (CHIRPS) is frequently used in research (Abdelmoneim et al., 2020). For this study, rainfall data from 2002 to 2022 were obtained from the CHIRPS website (https://www.che.ucsb.edu/data/chirps/). Moreover, Gridded soil data with a 250m spatial resolution were downloaded from the African Soil Data Information Service (AFSIS) website.

A total of 4500 ground truth data points for land use and land cover (LULC) classification and accuracy assessment were collected from the field through in-situ observations, with geo-location data obtained using a handheld Garmin GPS device and from Google Earth using a time slider image. Of these ground truth points, 738 were used for accuracy assessment of image classification with the error matrix, which allowed us to evaluate the kappa coefficient, overall accuracy, and the producer's and user's accuracy. Qualitative data were collected through interviews with 10 elderly key informants to supplement and triangulate the quantitative findings.

2.2.2 Spatial Multi-Criteria Analysis (MCA)

Analyzing land degradation status is challenging because combining different degradation indicators into a single index is complex (Bednář & Šarapatka, 2018). MCA can address this problem by integrating various indicators into a single index and ranking the performance of decision options against different standards (Hajkowicz, 2007; Saaty, 2008). The MCA process involves several steps: defining objectives, updating the requirements to measure objectives, selecting alternatives, converting criterion scales into comparable units, assigning weights to criteria based on their relative importance, applying a mathematical model to rank alternatives, determining the best alternative, and finally, combining different criteria into a single index (Ewunetu et al., 2021b; Jafari & Zaredar, 2010).

A Spatial MCA approach integrated with the AHP was used to assess land degradation severity. This method was selected because of its ability to synthesize multiple biophysical, climatic, and terrain variables into a single, comparable index. Pairwise comparison weighting was applied to ensure an objective ranking of the indicators, enhancing the reliability of the composite land degradation assessment(Ashtiani et al., 2009). This is a clear and dominant decision-making tool that links several objectives or indicators. Moreover, when MCA and AHP are combined with GIS, they form an effective technique for integrating different geospatial datasets to address environmental problems (Ewunetu et al., 2021b). This study employed the MCA and AHP methods integrated with GIS technologies (Fig. 2).

The most popular technique for criteria standardization in spatial MCA is linear scale transformation (Eastman, 2012), which was used here to simplify the interpretation process. Each criterion was normalized before being scaled to a number from 1 to 5, representing the degradation level from very low to very high. In spatial MCA, three popular weighing techniques was used: ranking, rating, and pairwise comparison (Malczewski, 2007; Prasad & Kousalya, 2017). Of these, the pairwise comparison method is one of the most frequently used in research (Saaty, 2008), and we apply this method here. The AHP procedure was used to generate raster data (maps); from which individual land degradation indicators and pairwise comparisons were made to determine the weighting of the criteria. In this instance, the less significant criterion receives the reciprocal value of the most significant criterion when the two criteria are compared.

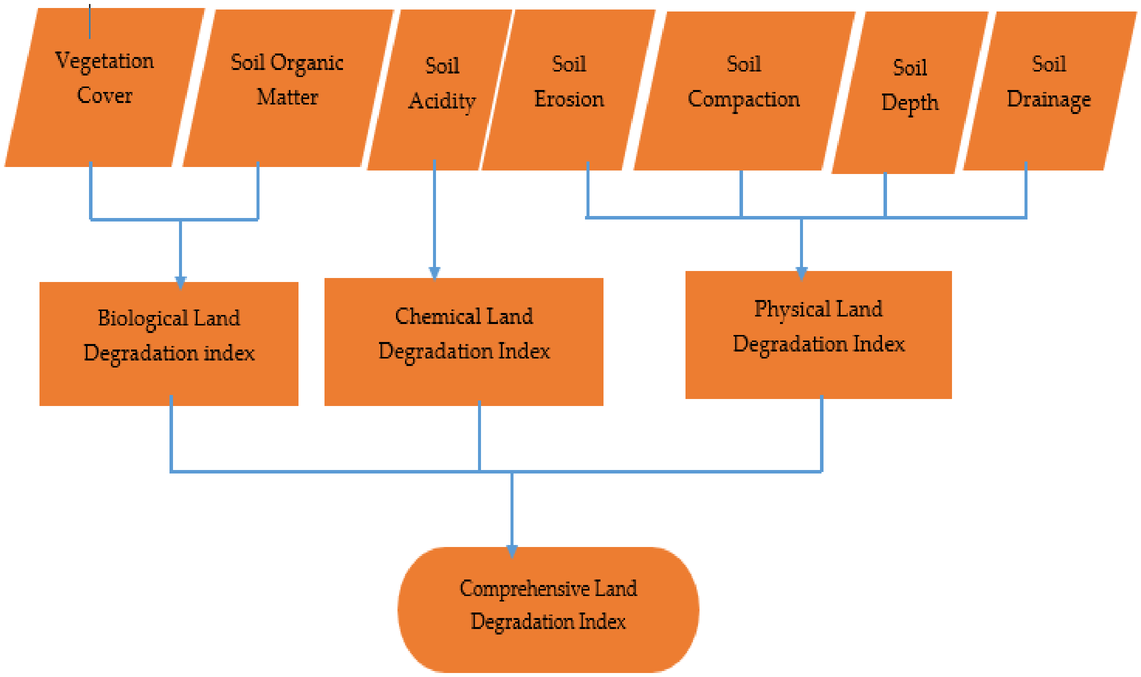

Fig. 2: Hierarchical structures of land degradation assessment in MCA in Choke Mountain

We use the comparison matrix's principal eigenvalue and its corresponding normalized right eigenvector to determine the relative importance of the criteria being compared. The elements of the normalized eigenvector are weighted with respect to the criteria or sub-criteria and rated with respect to the alternatives (Saaty, 2008). Next, the consistency level of the order matrix was evaluated. The comparisons were reexamined if the consistency index fell below a predetermined threshold. The criteria maps were then combined using the weighted overlay technique, which multiplied each standardized criterion by its weight in the weighted overlay process. ArcGIS10.5 was used for all geospatial processes in this study.

Develop Physically Degraded Land Indicators

Physically degraded land refers to the deterioration of the land's physical characteristics, such as structure, texture, and water retention capacity (Dagne et al., 2023). Soil erosion, soil compaction, soil drainage, and soil depth indicators were used to model a physically degraded land index.

Description of Soil Erosion Factorsand the RUSLE Model

Soil erosion is a major indicator of land degradation(Hurni et al., 2010). In the Ethiopian highlands, including the Choke mountainwatershed, a long history of human activity combined with rugged topography has made water erosion the primary cause of soil erosion (Eshetu & Abegaz, 2024). The RUSLE is a widely used model for estimating topsoil loss by water (Wischmeier and Smith, 1978). When integrated with GIS, it is a powerful tool for evaluating topsoil loss, especially in regions such as Africa, where data are often scarce. However, the model mainly addresses rill and inter-rill erosion while neglecting other types of erosion, such as landslides and gullies (Renard & Foster, 1985). The RUSLE model was employed to estimate the annual soil loss rate across the Choke mountain watershed. The RUSLE was chosen because of its simplicity and compatibility with GIS-based spatial analysis, making it particularly effective for large-scale land degradation assessments(Farhan & Nawaiseh, 2015). The model was parameterized using the equation proposed by Hurni (1985):

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

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where: A= Estimated annual soil loss ($tha^{-1}yr^{-1}$); R = Rainfall erosivity factor(MJ mm $ha^{-1}h^{-1}yr^{-1}$); K= Soil erodibility factor($tha^{-1}MJ^{-1}mm^{-1}$); SL = Slope length and steepness factor (unitless); C = Land cover management factor(unitless); P = Conservation practice factor (unitless).

Rainfall Erosivity (R-factor) is measured as the effect of rainwater on topsoil loss in a particular geographic area. Raindrop duration, intensity, and size, as well as the detaching force of rainfall hitting the soil surface and the presence of runoff, are all strongly correlated with topsoil loss (Wischmeier and Smith, 1978). However, the absence of automatic rain gauges in the research area prevented access to such data. Thus, 2002 years (2002–2022) of average annual rainfall data for this inquiry were downloaded from CHIRPS. The R-factor was computed using the following formula (Hurni, 1985):

$$R = -8.12 + 0.562(Pa) \quad (2)$$

where "R" refers to rainfall erosivity (MJ mm $ha^{-1}h^{-1}yr^{-1}$) and "Pa" refers to the average yearly rainfall(mm).

Soil Erodibility (K-factor) refers to the vulnerability of topsoil elements and surface materials to detachment and transport by raindrops and runoff(Laflen & Flanagan, 2013). The K-factor depends on soil characteristics such as permeability, texture, organic matter, structure, and overall soil biomass stability (Yang et al., 2018). Researchers have developed several formulas to determine the K-factor for evaluating topsoil loss in different regions (Gass & Fu, 2013). Among these, Equation 3 is widely used to estimate the K-factor in different landscapes. Accordingly, we compute the K-factor by applying the below equation (Ganasri & Ramesh, 2016).

$$K = \left\{0.2 + 0.3exp\left[0.0256SAN\left(1.0 - \frac{SIT}{100}\right)\right]\right\}\left(\frac{SIT}{CLY + SIT}\right)^{0.3}\left(1.0 - \frac{0.25C}{C + \exp(3.72 - 2.95C)}\right)$$
$$\left(1.0 - \frac{0.7\left(\frac{1-SAN}{100}\right)}{\left(\frac{1-SAN}{100}\right) + exp\left(-5.51 + 22.9\left(\frac{1-SAN}{100}\right)\right)}\right) \quad (3)$$

where, 'SIT' represents silt in %; 'C' refers to organic carbon in %; 'SAN' is the percentage of sand; and 'CLY' is the percentage of clay.

Topographic (LS-Factor)refers to the effect of topography on soil erosion.Slope length (L) and slope gradient (S) factors are joined in a single index, the LS-factor, to describe the topographic factor for soil loss (Ganasri & Ramesh, 2016). The slope's length and gradient greatly affect the volume and pace of topsoil loss in a specific area. Because surface overflow volume and velocity rise with inclination of the surface and slope distance, the topsoil loss likewise rises (Renard & Foster, 1985; Teferi et al., 2013). The following equations were used to create the LS factor map for this study:

$$L = \left(\frac{\lambda}{22.13}\right)^m \quad (4)$$

$$m = {}^{F}/_{(1+F)} \quad (5)$$

$$F = \frac{{}^{\sin\beta}/_{0.896}}{3.0(\sin\beta)^{0.8} + 0.56} \quad (6)$$

Here, λ represents the product of flow accumulation and cell size, L is the slope length factor, m is the slope length exponent, F is calculated under conditions where the soil is moderately susceptible to both inter-rill and rill erosion, and β is the slope angle in degrees (slope in degrees * 0.01745).

$$S = 16.8 * \sin\beta - 0.05 \quad \delta \geq 9\% \quad S = 10.8 * \sin\beta + 0.03 \quad \delta < 9\%$$
(7)

Cover Management (C-Factor) reflects how soil cover, such as grass and tree cover, on non-agricultural land and conservation practices on agricultural land can reduce topsoil loss (Molla & Sisheber, 2017). The C-factor for this study was derived from the land use and cover (LULC) map (Fig. 6a), created using Landsat 8 imagery from January 2022 through supervised classification in ArcGIS. After classification, the raster map was converted to vector format to assign C-factor values for each LULC type based on suggestions in previous literature (Table 1). Finally, the C-factor map was transformed into a raster layer using the raster conversion tool in ArcGIS10.5.

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Table 1: C-factor for different LULC types

LULC	C-value	Sources
Dense Forest	0.01	(Bewket & Teferi, 2009; Ewunetu et al., 2021b)
Shrub and bush	0.20	(Eshetu & Abegaz, 2024; Ewunetu et al., 2021b)
Grazing land	0.05	(Hurni,1985)
Cultivatted land	0.15	(Tiruneh & Ayalew, 2015)
Barren land	0.60	(Bewket & Teferi, 2009; Ewunetu et al., 2021b)
Waterbodies	0.00	(Ewunetu et al., 2021b)

Support practice (P-Factor) refers to soil erosion management practices, such as terracing, contour farming, and strip cropping, to reduce soil erosion (Eshetu & Abegaz, 2024; Ewunetu et al., 2021b). During our on-site observation, we found that the terrace structure was widely used in the watershed; however, it had poor function due to inadequate support and maintenance. Accordingly, using a terrace to determine the P-factor for this study was deemed impractical. Thus, we calculated the P-value using an alternative method that combines LULC and DEM, as suggested by Wischmeier and Smith (1978). Then, we classified the catchment into agricultural and other land use types to determine P-factors. Agriculture land was also classified into six slope classes. A P-value was given to individual classes, while all other LULCs were assigned a value of 1 (Table 2).

Table 2: P-Factor of conservation practices (Bewket & Teferi, 2009)

Land use type	Slope (%)	P-value
Agricultural land	0-5	0.1
	5-10	0.12
	10-20	0.14
	20-30	0.19
	30-50	0.25
	50-100	0.33
Non-agricultural land	0-100	1

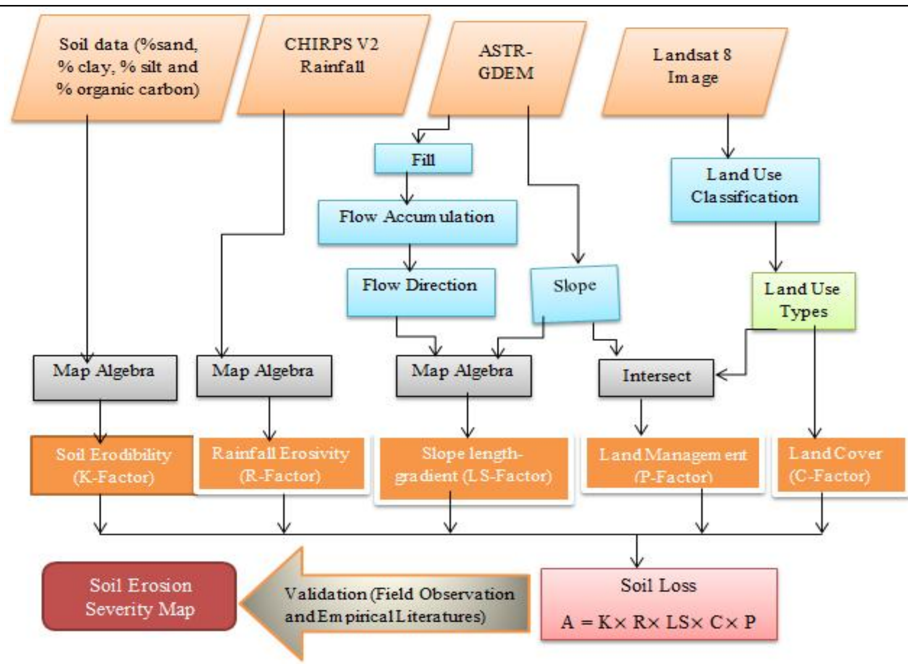

Fig. 3: Flow chart showing the methodology for soil loss estimation.

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Finally, as shown in Fig. 3 and Equation 1, the topsoil loss in Choke Mountain was calculated by multiplying the five RUSLE variables after resampling to 30m by 30m spatial resolution. After evaluating the spatial severity of the topsoil loss, the raster map was reclassified into six severity levels (Ewunetu et al., 2021b; Teferi et al., 2013; Yesuph & Dagnew, 2019).The validity and consistency of the model's output were tested by comparing it with empirical research conducted in the Ethiopian highlands and field observations. The colored topsoil loss severity map (Fig. 8) was printed and taken to the field for verification.

Soil drainagerefers to the amount and speed of water movement in the soil, including both lateral and surface-level runoff. Waterlogging and crusting have a considerable influence on soil morphology, with significant consequences (Abdelrahman et al., 2016). Typically, soil drainage is classified into seven distinct classes based on the rate of water extraction from the soil (USDA, 2017). In this study, the raster map of soil drainage obtained from AFSIS was reclassified according to the values presented in Table 3.

Table 3: Soil drainage classes (Hengl et al., 2017)

Drainage class	Level drainage	Level description
1	Very poor	Drained Excessively
2	Poor	Drained Somewhat Excessively
3	Imperfect	Well Drained
4	Moderate	Well Drained moderately
5	Well	Drained Somewhat Poorly
6	Somewhat excessive	Poorly Drained
7	Excessive	Drained Very Poorly

Soil compaction is a is a primary sign of physical land degradation (Oldeman, 1994). It is described as the weight of oven-dried soil for each unit of topsoil volume and happens when pressure is exerted on the soil surface (Nawaz & Bourrié, 2013). Soil bulk density has been used to calculate soil compaction (Bhagat et al., 2014). The soil bulk density map in raster format was downloaded from AFSIS and then sorted according to the value ranges in Table 4 to assess compaction levels in Choke Mountain.

Table 4: Soil compaction level (USDA, 2008)

Bulk density class	Compaction Status
< 1 g/cm^3	Low compacted soil
1-1.25 g/cm^3	Medium compacted soil
1.25-1.55 g/cm^3	High compacted soil
> 1.55 g/cm^3	Very high compacted soil

Soil depth is a crucial indicator of physical soil quality (USDA, 2008). Shallow-depth soil often exhibits higher degradation and present physical constraints that limit crop rooting depth. Deeper soil is more helpful to plant root growth and development because it generally contains more nutrients and moisture (Eastman, 2012). For this study, soil depth was estimated using a raster soil depth map obtained from AFSIS and reclassified into standard classification levels (Table 5).

Table 5: Soil depth classes (USDA,2008)

Soil depth class	Degradation level	Level Description
Less than 30cm	Very high	Soil has very shallow deepth
From 30 to 50cm	High	Soil has shallow deepth
From 50 to100cm	Moderate	Soil has moderately deepth
From 100 to150cm	Low	Soil has high deepth
Grearer 150 cm	Very Low	Soil has very deepth

Develop Biologically Degraded Land Indicators

Biological land quality can be evaluated using different indicators.Frequently used indicators to develop biological land quality index include soil organisms, vegetation cover, and organic matter in the topsoil (Qi et al., 1994). As a result, we used vegetation cover and soil organic matter to map and quantify the biologically degraded land index.

Soil Organic Matter (SOM) is one of the key constituent of soil that significantly influences biological land quality and ecosystem stability (Malav et al., 2022; Oldeman, 1994). Typically, SOM is measured in laboratory. Though, due to financial constraints, measuring SOM directly at the watershed level was not feasible for this study. Thus, SOC raster map from AFSIS was used to generate SOM. SOM contains 58% organic carbon by weight. Using equation 8, we converted SOC raster map to SOM using the map algebra raster calculator following Combs and Nathan (Combs et al.,1998). Then, the SOC raster map was reclassified based on a scientific classification method (Table 6).

$$Percentage\ of\ Organic\ Matter = Percentage\ of\ Total\ Organic\ Carbon\ x\ 1.72 \quad (8)$$

Table 6: Classes of soil organic matter in soil (Eastman, 2012)

Category in %	Description
< 0.2	Very poor soil organic matter content in the soil
0.2-0.6	Low level amount of organic materials in the soil
0.6-1.2	Medium soil organic matter contentin soils
1.2-2.0	High level amount of soil organic matter
>2.0	Extremelyhigh amount of organic materials in the soil

Vegetation Cover is the main indicator for evaluating biologically degraded land because it reflects vegetation cover and biomass productivity (Ewunetu et al., 2021b). Adjusted Vegetation Index (SAVI) is an extensively utilized remote sensing data index for evaluating vegetation buffers. SAVI is particularly suitable in areas with significant bare soil, where the NDVI may be less effective due to its sensitivity to soil brightness (Olsson & Tengberg, 2018). In this study, SAVI was calibrated using Landsat 8, following the methodologies used by Ewunetu et al. (2021).

$$SAVI = \frac{(NIR-RED)}{(NIR+RED+L)}(1+L) \quad (9)$$

Here, RED refers to reflectance in the visible red spectrum, while NIR represents near-infrared reflectance. L is the vegetation density coefficient, ranging from 0 for very dense plant cover to 1 for very sparse cover. We tested several values for L, including 0.25, 0.5, and 0.75, based on recommendation (Qi et al., 1994). After visually interpreting the image (Qi et al., 1994) and considering previous studies (Ewunetu et al., 2021b),we chose L = 0.5 as the middle value for this research analysis.

Develop Chemical Degraded Land Indicators

Soil chemical degradation describes unintended alterations in the chemical characteristics of soil brought on by a reduction in soil quality (Osman, 2013). Key indicators of chemical quality of land include soil acidity, salinity, and sodicity (Nachtergaele et al., 2008).Since the study location is humid and chemical fertilizer application and crop residue removal are prevalent, we only take soil acidity indicator into account in this study. The study location is characterized by high humidity, with widespread practices of chemical fertilizer application and crop residue removal(Ewunetu et al., 2021c). The pH value of the soil solution in water serves as an indicator for determining soil acidity.Soil acidity is defined as the quantity of hydrogen ions (H^+) in the soil, which establishes the pH level of the soil (Nachtergaele et al., 2008). A soil pH raster map from AFSIS was obtained and categorized using a recognized soil pH classification system to determine the state of soil acidity level in the research area (Table 7).

Table 7: Category of soil acidity level based on pH value(Nachtergaele et al., 2008).

PH value	Description
< 5.5	Veryacidic soils
5.5 - 6.7	Soils that are somewhat acidic
6.7-7.3	Soils that are neutral

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7.3-8.0	Soils that are somewhat alkaline
> 8.0	Extremely alkaline soils

III. RESULTS AND DISCUSSION

Physical Land Degradation Indicators

Estimation of Annual soil loss using RUSLE model

Soil erosion has been estimated using the RUSLE model, which incorporates rainfall erosivity, soil properties, topography, LULC, and management practices. The factors used to calculate are discussed here below. Rainfall erosivity (R-factor) was derived from precipitation using equation 2. The spatial distribution of the R-factor in the study area expanded from 610 to 1216 MJ mm $ha^{-1}h^{-1}yr^{-1}$. Shower rainfall type is a common feature in the highland region, indicating that the power of the rainfall is higher in the lowland areas. As a result, the bottom part has higher erosivity values than its middle and top parts (Fig. 4). The relative erosivity is allied with more rainfall power to erode the soil surface (Belayneh et al.,2019; Gelagay, 2016).

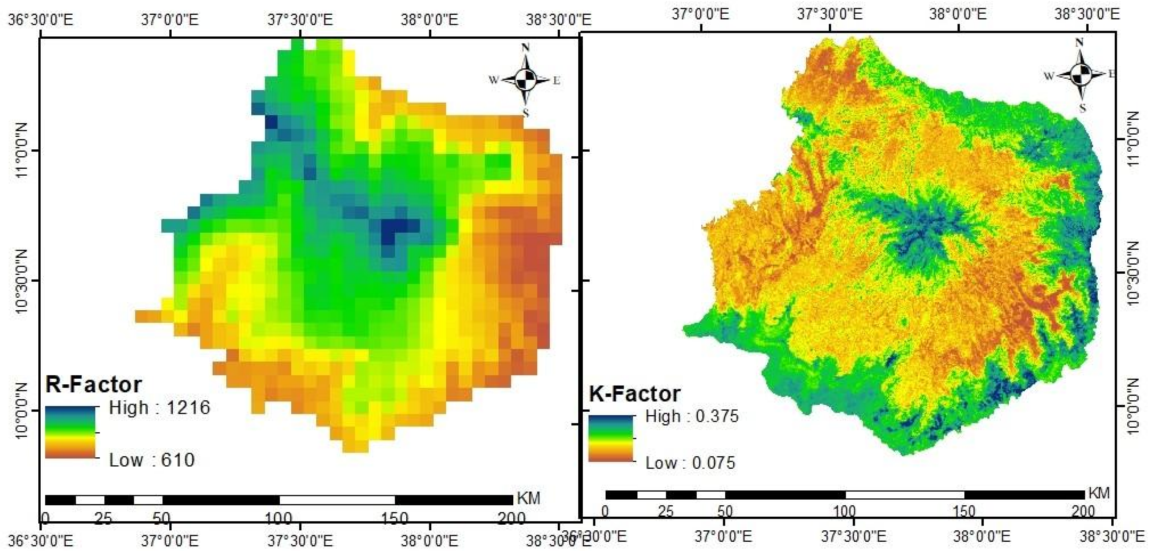

Fig. 4: Rainfall erosivity (right) and soil erodiabilty (left) in Choke Mountain.

The soil erodibility(K-factor) for the study area was calculated using Equation 3, based on soil characteristics including silt, clay, sand, and organic carbon content (Ewunetu et al., 2021). The result indicated that soil erodibility value in the Choke mountain watershed was ranged from $0.075 tha^{-1}MJ^{-1}mm^{-1}$ on upper and lower to $0.375 tha^{-1}MJ^{-1}mm^{-1}$on the middle part (Fig. 4). The lower value of K is allied with the soils having low precursor moisture content and a permeability (Ganasri & Ramesh, 2016).

The LS-value was calculated by multiplying the slope length (L) and steepness(S) values after determining the L and S values. The LS-factor value in Choke Mountain ranged from 1 to 109 (Fig. 5).The majority of the mountain watershed, though, has an LS value of less than 10, which found in the middle part. The LS-factor significantly influences soil loss in the lower part of the watershed, whereas its impact is limited in the middle and upper parts due to the gentler slopes.

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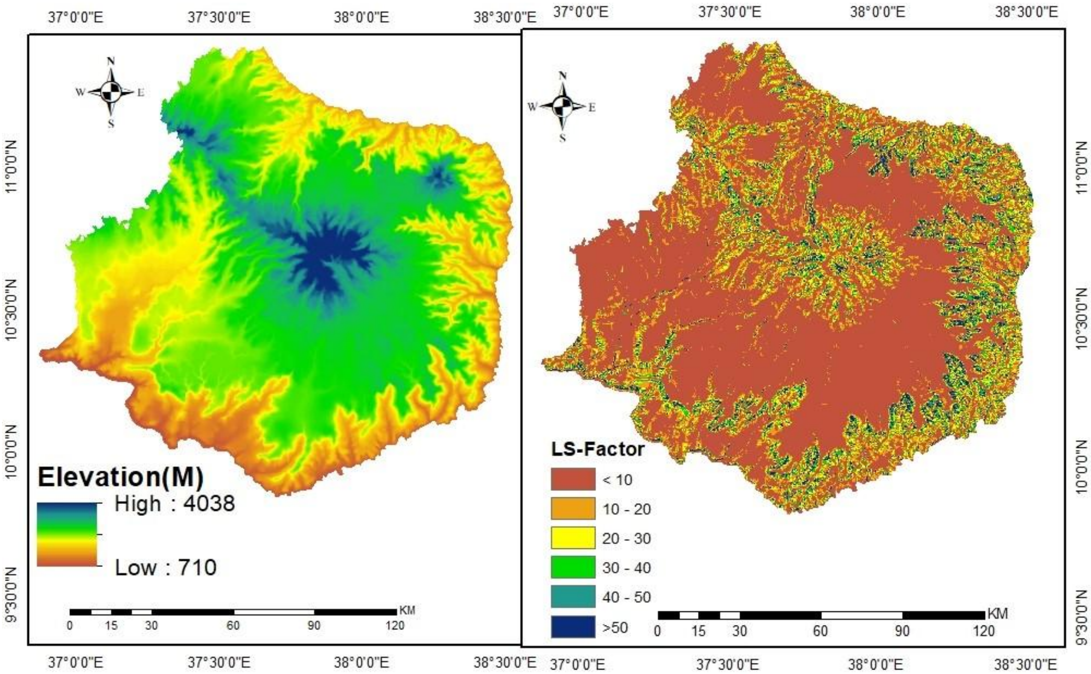

Fig. 5: Elevation (right) and LS-factor (left) maps of the Choke Mountain

The Cover management(C-factor) for the study was derived from LULC map (Fig. 6 and Table 1). The overall classification accuracy of the LULC map was 90%, with a kappa coefficient of 0.87. The results show that the C-factor values in the Choke Mountain ranged from 0.01 in forested areas to 0.6 in barren land surface (Fig. 6). A lower C-factor value, such as 0.01, indicates dense vegetation cover and thus lower vulnerability to soil erosion. In contrast, higher C-factor values represent areas with sparse vegetation, making them more susceptible to soil erosion (Ewunetu et al., 2021). These findings are consistent with a previous study conducted in the northwestern Ethiopian Highlands (Belayneh et al., 2019).

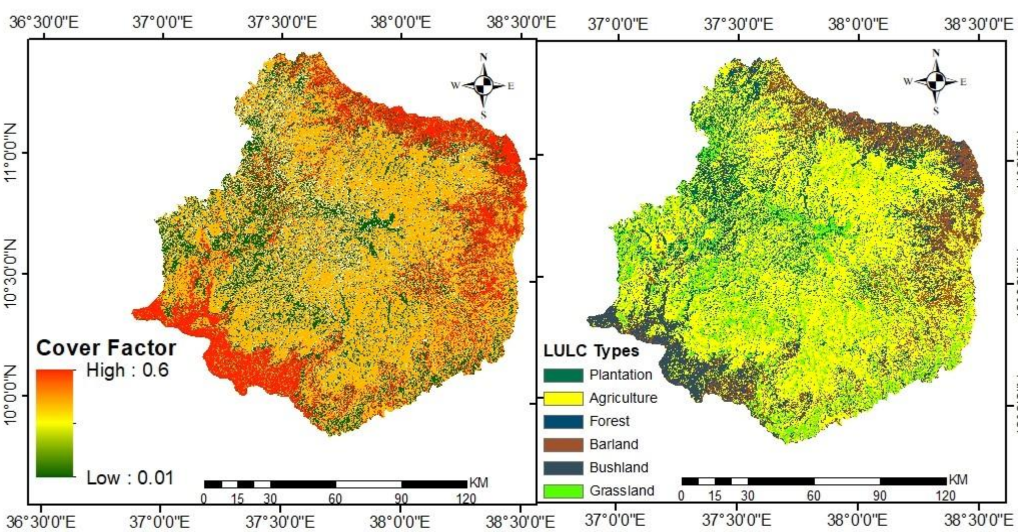

Fig. 6: Cover factor values (right) and LULC types (left) in Choke Mountain

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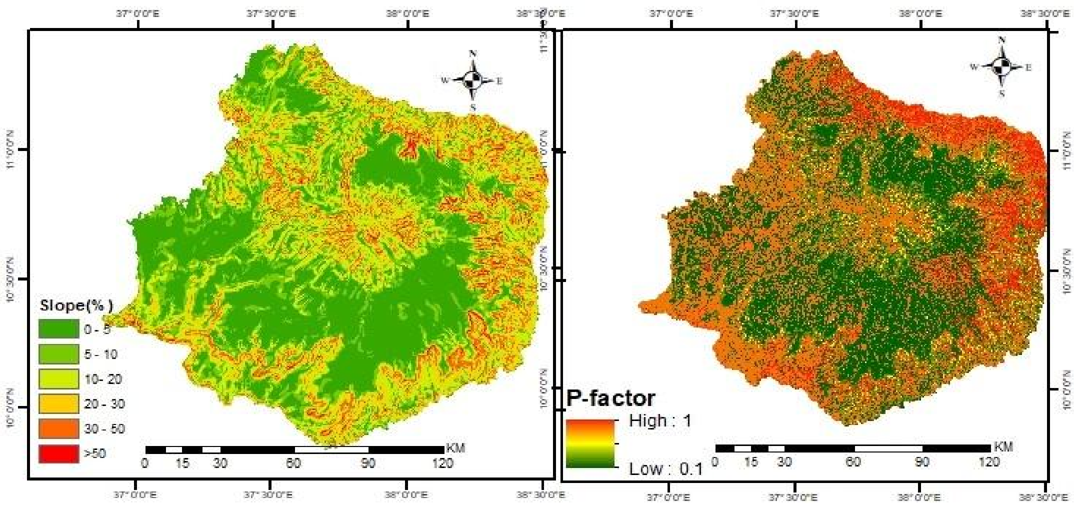

Fig. 7: Slope class (right) and management values (left) in the Choke Mountain.

The Support Practice (P-factor) in this study was derived from the correlation between slope percentage and LULC types. It was ranged from 0.1 to 1 across the study area. As shown in Fig. 7b, a P-value of 1 is observed in the lower parts of the watershed. In contrast, lower P-values (as low as 0.1) are predominant in the lower and upper sections of the watershed. Higher P-values indicate areas primarily covered by bush, shrubland, and grazing land scant, where soil erosion control measures are largely absent (Ewunetu et al.,2013; Gelagay and Minale, 2016).

Finaly, each layer of the RUSLE parameters was organized in a grid format with a cell size of 30 m by 30 m, and a soil loss map of the watershed was produced (Fig.8).According to the model's outcome for these variables, the central portion of the watershed has lost topsoil at a rate ranging from 0.01 to 75t $ha^{-1}yr^{-1}$, and soil loss rates in upstream and downstream zones as well as in some erosion hotspot locations surpass 75t $ha^{-1}yr^{-1}$ (Fig.8). As indicated in Table 8, about 15.25% and 20.3% of the watershed experienced a very low and low soil loss rate, ranging from 0-5 t $ha^{-1}yr^{-1}$ and 5-15t $ha^{-1}yr^{-1}$, respectively. The result shows that about 13.55% of the watershed experienced soil loss ranging from 15 to 30t $ha^{-1}yr^{-1}$, which is characterized as a moderate erosion rate. Further, about 28.12% of the watershed lost topsoil with rates from 30 to 75t $ha^{-1}yr^{-1}$, indicating a high to very high soil loss rate. The remaining 22.52% of the watershed was under severe erosion rate with soil loss exceeding 75t $ha^{-1}yr^{-1}$ (Table 8). As shown in Table 8, the area under high to severe soil loss class covers about 35.9% area of the watershed, found in most upper and lower parts in very steep-sloped areas (Fig.7).

The average annual soil loss of the entire Choke Mountain watershed was estimated at 44t $ha^{-1}yr^{-}$which is generally greater than the tolerable soil loss of two times the maximum(18t $ha^{-1}yr^{-1}$) soil loss tolerance value given by Hurni (1985) for the Ethiopian highlands. It implies that a total of 65.2 million tons of soil has been lost annually from the entire watershed. Any soil loss rate greater than 10t $ha^{-1}yr^{-1}$ soil loss rate will not be restored in a period of 5 to 10 decades (Kouli and Soupios, 2009). Accordingly, nearly half of the Choke Mountain watershed was beyond the threshold of soil loss tolerance level (Table 8).

Table 8 Annual soil loss class and risk levels in choke mountain watershed

Soil Loss (t/ha/yr.)	Area (ha)	Percentage	Severity level	Assigned value	Risk level
<5	304972.55	15.25	Very slight	1	Very Low
5-15	405963.46	20.3	Slight	2	Low
15-30	270975.61	13.55	Moderate	3	Medium
30-50	221780.038	11.09	High	4	High
50- 75	340569.346	17.03	Very high	5	Very high
>75	450359.464	22.52	Sever	5	Very high

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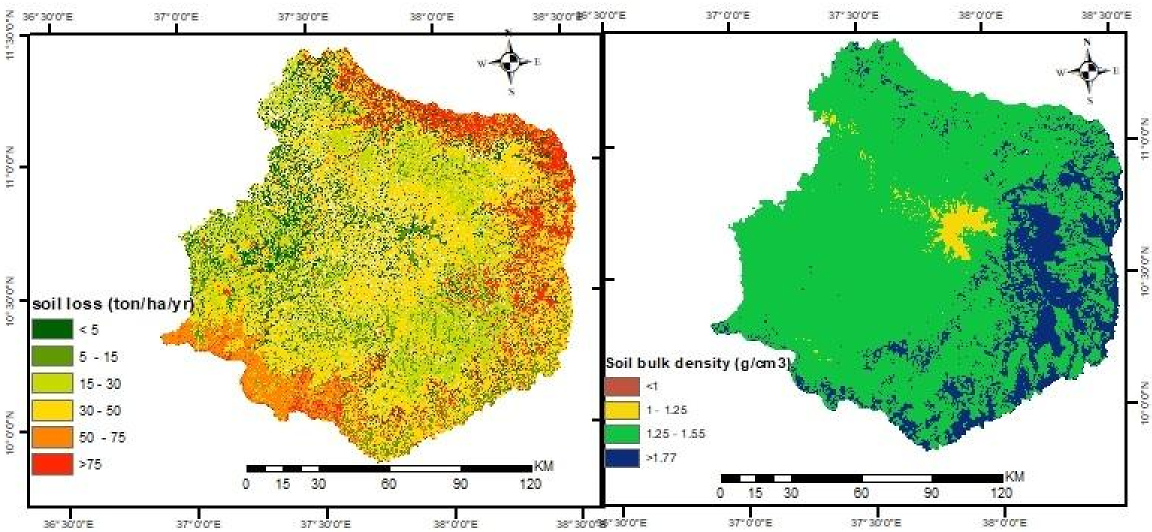

Fig.8: The annual soil loss (right) and soil bulk density (left) of the Choke mountain watershed

Consistency and validation of estimationthe model: In comparison to field observations and results from earlier experimental research, the estimated average soil loss rate and spatial patterns in this study are generally accurate. Based on field evaluations of rill and inter-rill erosion, Bewket and Sterk (2003) reported annual soil loss ranging from18 to 79 t $ha^{-1}yr^{-1}$in parts of the same and adjacent watersheds. Similarly, five years of monitoring in an experimental micro-watershed (Anjeni), located within the study area, showed that soil loss from cultivated fields under traditional land-use practices ranged from 17 to 176t $ha^{-1}yr^{-1}$ (Herweg and Ludi, 1999). More recently, Belayneh et al. (2020) found mean soil loss rates of23.5, 45.6, and 58.1t $ha^{-1}yr^{-1}$for new, old-graded soil bund-treated, and non-treated plots, respectively, based on experimental studies in cultivated land of the Gumara sub-watershed, which lies within the present study area.Hurni (1993) estimated the average soil loss from cultivated fields in the Ethiopian highlands at42t $ha^{-1}yr^{-1}$accounting for re-deposition of mobilized sediment. To validate the model results, selected field observations were conducted. During this process, the color-printed soil erosion severity map generated from the model was compared with actual conditions on the ground.

The estimated soil loss rate obtained in this study is also consistent with empirical evidence from previously published studies. For example, 24.3t $ha^{-1}yr^{-1}$ average soil loss was reported in the Gelana sub-watershed, north Wollo (Miheretu & Yimer, 2018); similarly, about 23.7 t $ha^{-1}yr^{-1}$ attested in the Geleda watershed (Gashaw et al., 2017); and nearly 24.9t $ha^{-1}yr^{-1}$ reported in the Enfraz watershed (Tiruneh and Ayalew, 2015). Similarly, the study conducted soil loss from the entire upper Blue Nile basin confirmed about 27.5t $ha^{-1}yr^{-1}$(Haregeweyn et al., 2017). Comparable results were also reported from the JabiTehinan district in West Gojjam Zone, with 30.6 t ha^{-1} yr^{-1}(Amsalu and Mengaw, 2014).

On the other hand, the findings of this study are largely consistent with recent empirical research. For example, mean soil losses of about 47.4 t ha^{-1} yr^{-1} and 42 t ha^{-1} yr^{-1} were reported for the Koga watershed in the Upper Blue Nile Basin(Molla and Sisheber, 2016;Gelagay and Minale, 2016); documented an average of 49 t ha^{-1} yr^{-1} in Dembecha District, West Gojjam (Zerihun et al., 2018). However, other studies conducted in various parts of Ethiopia reported considerably higher average soil loss rates than those found in this study.For instance, Zeleke (2000) estimated a mean soil loss of 243 t ha^{-1} yr^{-1} in the northwestern Ethiopian highlands, attributed to rugged topography, low vegetation cover, and the absence of land management technologies. Similarity, about 93t $ha^{-1}yr^{-1}$ average soil loss was reported in the Chemoga watershed (Bewket and Teferi, 2009); 84t $ha^{-1}yr^{-1}$ average soil loss in northwestern Ethiopia found by Selassie and Belay (2013); and 75t $ha^{-1}yr^{-1}$ in the entire upper Blue Nile Basin (Tamene et al., 2017).Overall, the empirical evidence suggests that although soil erosion is a widespread problem in the Ethiopian highlands, quantitative estimates remain variable and sometimes inconsistent. These discrepancies may arise from methodological differences

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among studies as well as variations in key erosion drivers such as rainfall, soil properties, topography, land management practices, and land-use types.

Soil compaction: The spatial distribution of soil compaction in the watershed ranged from 1 to 1.55 g/cm^3. On the other hand, Table 9 indicates that 80.24% of the watershed soil bulk density was between 1 and 1.25 g/cm^3, indicative of medium compaction (Fig.8). The outcome demonstrates that a significant portion of the watershed's soil compaction status can be categorized as medium, which can be linked to the absence of intensive machine farming in the region. In cooler climate zones and regions with more vegetation cover, which are prevalent in mountainous regions with high precipitation rates and low temperatures, little soil compaction was seen. The findings suggest that soil compaction wasn't a major issue in the Choke Mountain Watershed.

Table 9: Statistics for physical land degradation indicators

Factor	Classes	Area (Ha)	Percentage	Assigned value	Degradation level
Soil bulk density (g/cm^3)	< 1	9998.10	0.50	1	Very Low
	1-1.25	40392.32	2.02	2	Low
	1.25-1.55	1604495.12	80.24	3	Moderate
	1.55-1.77	344934.46	17.25	4	High
Level of drainage	Poor	0.06	0.00	1	Very low
	Imperfect	3502.61	0.18	2	Low
	Moderate	138876.79	6.96	3	Moderate
	Well	370223.85	18.56	4	High
	Somewhat excessive	1433703.58	71.88	5	Very high
	Excessive	0.06	0.00	6	Very high
Soil depth class (cm)	25-30	722.96	0.04	5	Very high
	50-100	329127.34	16.50	4	High
	100- 150	872992.35	43.77	3	Moderate
	150-200	791777.82	39.70	2	Low
	>200	722.96	0.04	1	Very low

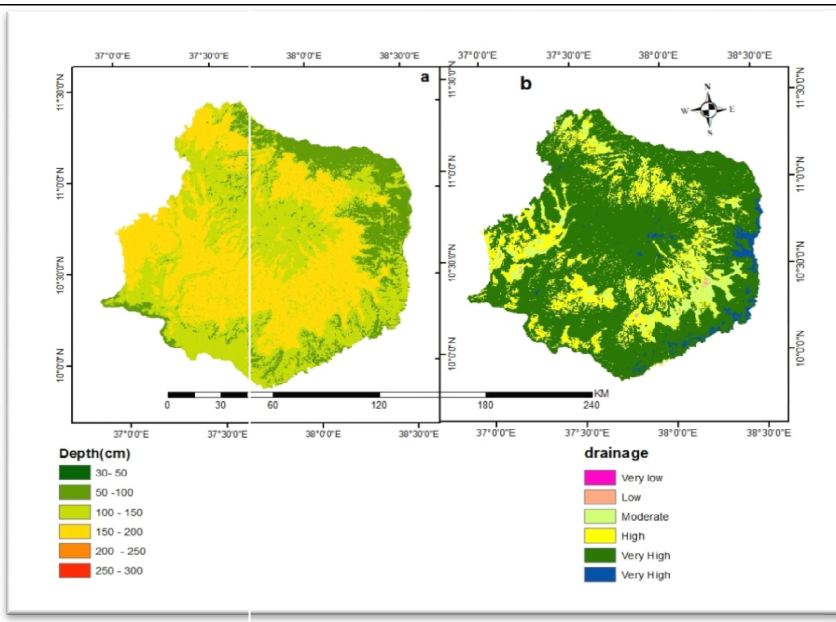

Fig.9: Soil bulk depth (right) and soil drainage (left) in Choke mountain watershed

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Soil drainage: as can be observed from Table 9, the sub-basin has good drainage characteristics in around 74.4% of its area. Figure 9 depicts the spatial pattern of soil drainage in the watershed. The final product and the impression of local land users in the Amhara regional state are comparable to the soil drainage map created by the agricultural transformation agency (ATA, 2017).

Soil depth: The watershed's spatial soil depth distribution ranged from 25 to 175 cm (Fig.9). According to Table 9, approximately 43.77% of the watershed has extremely deep soils (>150 cm), indicating very little land degradation, whereas approximately 39.7% of the watershed has shallow soil, ranging from 25 to 30 cm, indicating extremely high degradation. While the lowest portion of the area has very shallow soil, reflecting higher erosion rates and more soil degradation, the majority of the midland areas are characterized by high soil depth.

The State of Physical Land Degradation

Using a pairwise comparison method, the weights of four indicators; soil erosion, soil compaction, soil drainage, and soil depth; that influence physical land degradation were determined. Weights were assigned to each subclass based on their relative impact on land degradation. The consistency ratio of the derived pairwise comparison matrix was 0.01, indicating a high level of consistency in the comparison.Overlay analysis resultrevealed that 70.7% of the watershed exhibited a moderate level of physical land degradation. The pairwise comparison results (Table 10) showed that soil drainage was the most influential indicator, followed by soil depth, soil erosion, and soil compaction. This indicates that the majority of the watershed is moderately degraded in terms of physical parameters (Fig. 10).Areas with low vegetation cover were commonly associated with shallow soil depth due to severe soil erosion. Local farmers also reported key physical land degradation issues during both formal and informal discussions, highlighting low soil infiltration rates, reduced soil depth, and increased soil erosion. Farmers noted that soil compaction has become a growing concern, as it reduces water infiltration and accelerates erosion. Soil depth reduction was attributed to runoff-induced erosion and continuous cultivation, particularly on steep slopes and croplands.These findings suggest that physical land degradation is intensifying in the Choke Mountain watershed. Similar observations were made by (Haregeweyn et al., 2017), who identified water-induced soil erosion as the primary cause of land degradation in the upper Blue Nile basin.

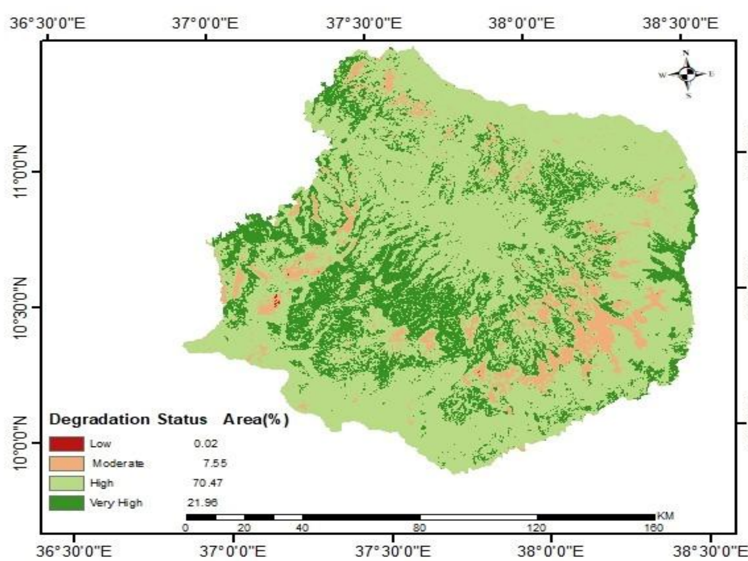

Fig.10: State of physical land degradation in Choke mountain watershed

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Table 10: Matrix for pairwise comparisons of markers of physical land deterioration

Criteria	Soil drainage	Soil depth	Soil Erosion	Soil compaction	Criteria Weighting
Soil drainage	1	2	3	5	40
Soil depth	0.5	1	2	3	30
Soil Erosion	0.33	0.50	1	3	20
Soil compaction	0.2	0.33	0.33	1	10

Biological Land Degradation Indicators

Vegetation Cover: The spatial distribution of vegetation indices in the Choke Mountain watershed ranged from **-0.2 to 0.92**(Fig. 11). According to Table 11, about **41.47%** of the watershed exhibited**moderate vegetation cover,** while **35.52%** had**poor vegetation cover.** These zones correspond to areas with**moderate**and**high levels of land degradation,** respectively. Additionally, nearly**one-third of the watershed**was classified as having**high to very high land degradation**based on vegetation indicators (Table 11 and Fig.11). The severity of degradation was more pronounced in the**lowland areas**than in the**highland regions,** particularly where**plantations and grazing lands were sparsely distributed.**

Table 11: Mean soil-adjusted vegetation index (SAVI) statistics

SAVI classes	Area (ha)	Area (%)	Cover Status	Assigned values	Degradation level
< 0.1	85992.26	4.30	Very poor	5	Very high
0.1-0.2	710336.07	35.52	Poor	4	High
0.2-0.3	829325.35	41.47	Moderate	3	Moderate
0.3.- 0.4	327170.55	16.36	High	2	Low
> 0.4	46995.77	2.35	Very high	1	Very low

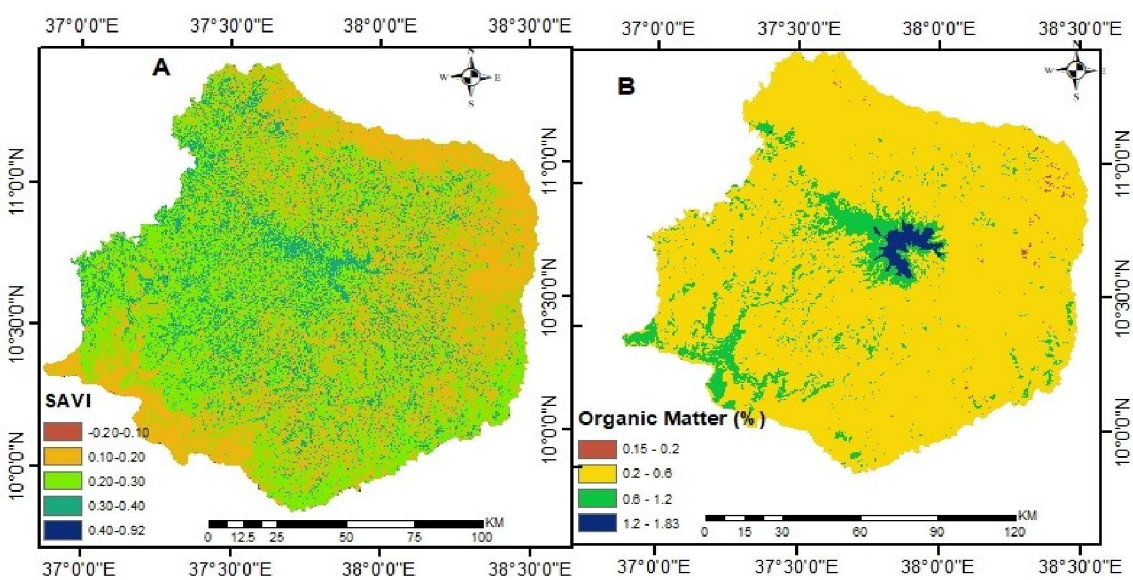

Fig.11: Soil Adjusted Vegetation Index (A) and soil organic matter (B) in Choke Mountain.

The status of soil organic matter (SOM): In the Choke Mountain watershed, soil organic matter (SOM) content ranged from 0.15% to 1.87%(Fig. 11). As shown in Table 12, about 89.02% of the watershed recorded SOM values between 0.2% and 0.6%, which are considered low and indicative of significant soil degradation. Such low SOM levels

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are often linked to increased soil erosion and declines in soil microbial activity. Conversely, higher SOM values reflect soils enriched with humus and organic residues from decomposed plant and animal matter.The prevalent low SOM levels in the watershed are likely due to continuous cultivation and the removal of crop residues for purposes such as household energy, livestock feed, and construction materials, which reduce organic matter inputs and ultimately diminish soil fertility.

Table 12: Levels of soil organic matter of topsoil in tht Choke mountain watershed

Category(%)	Area (Ha)	Percentage(%)	Level of SOM	Severity level	Assign value
0.15- 0.2	5199.532	0.26	Very low	Very high	5
0.2-0.6	1780239.764	89.02	Low	High	4
0.6-1.2	190182.882	9.51	Medium	Moderate	3
1.2-1.86	23997.84	1.20	High	Low	2

The Status of Biological Land Degradation

The weights of the two indicators influencing biological land degradation, vegetation cover and soil organic matter, were determined using a pairwise comparison matrix, similar to the procedure applied for indicators of physical land degradation. Based on the relative impact of each subclass on land degradation, appropriate weights were assigned. As shown in Table 13, vegetation cover was a less significant predictor of biological land degradation in the Choke Mountain Watershed than soil organic matter. The estimated pairwise comparison consistency ratio was 0.01, indicating a perfectly consistent and valid comparison. The weighted overlay analysis presented in Figure 12 reveals that 37.4% and 55.5% of the watershed experienced low to moderate levels of biological degradation. This implies that nearly half of the watershed has been affected by low to moderate biological degradation, primarily due to declining vegetation cover and reduced soil organic matter. These findings align with the perceptions of local land users. Farmers reported during both formal and informal discussions that excessive exploitation of natural resources has led to a gradual decline of both flora and fauna on their farmland. Furthermore, respondents emphasized that soil nutrient depletion caused by water erosion remains a persistent and unresolved form of land degradation.However, the findings of this study are consistent with those of Ewunetu et al. (2021), who conducted a study in the north Gojjam sub-basin

Table 13: A comparison matrix of the biophysical indices of land degradation

Criteria	Organic matter	Vegetation cover	Criteria weighting
Organic matter	1	3	70
Vegetation Cover	0.33	1	30

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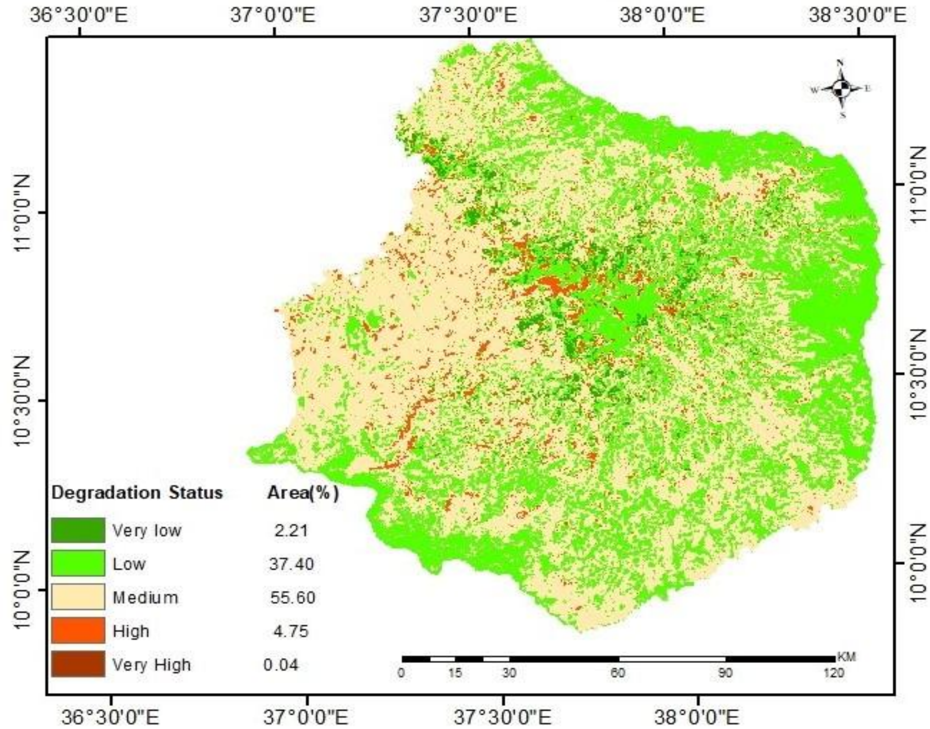

Fig.12. Biological land degradation status in the choke mountain watershed

The State of Chemical Land Degradation

The spatial variation of chemical land degradation in the form of soil acidity in the Choke mountain watershed varied from 5 to 7.8 pH values (Fig 12 and Table 14). The result shows that soil acidity level for about an area covered about 4% was less than 5.5 pH value which is considered as high. High soil pH concentration is found in the Choke Mountain reserved area, where wet climate condition and water availability is higher as well as the area covered by natural forest and afro-alpine grass. Wet climate and high rainfall leach soluble nutrients from the soil, such as calcium and magnesium which are specifically replaced by aluminum and increased potential for acidic soils (Abate et al., 2017). The decomposition of organic matter produces hydrogen ions, which are responsible for soil acidity formation (Golla, 2019).

About 37.4% part of the watershed experienced soil acidity ranged from 5.5 to 6.7 pH value, which expressed a high level of degradation (Table 14). As Figure 13 observed most highland and midland parts of the watershed, in which continuous agriculture activity and continuous application of chemical fertilizers takes place, as well as eucalyptus plantation being common, were vulnerable to soil acidity. This might be from the application of acid-forming fertilizers and over-cultivation. According to local experts, due to population growth and persistent demand for food and fuel, the removal of agricultural by-products (crop residues) and continuous crop harvest, and the use of acid-forming inorganic fertilizers are important contributions for increasing soil acidity in the sub-basin. Continuous application of chemical fertilizers with nitrogen and/or phosphorus nutrients only in the form of diammonium phosphate (DAP) and urea has adversely affected soil chemical properties (Golla, 2019). Land used for eucalyptus fields is the most affected by soil acidity (Abate et al., 2017).

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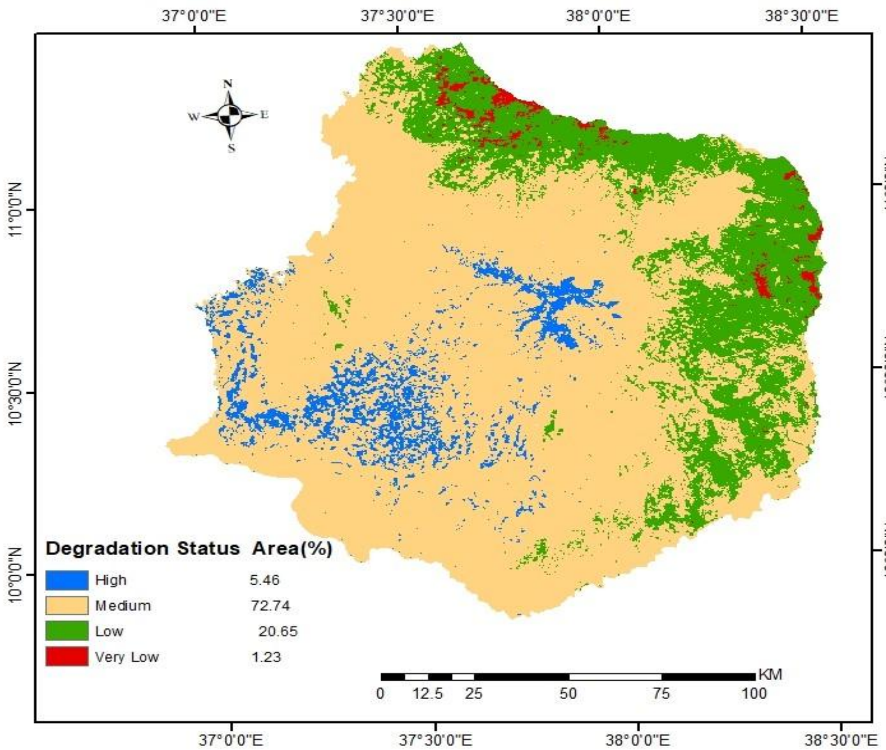

Fig. 13: Soil acidity statuses in the Choke Mountain

However, the majority of the area (55.6%) soil pH value varied from 6.7 to 7.3, a range that is considered neutral, whereas the pH value for the remaining 1.23% of the watershed ranged from 7.3 to 7.8, which is characterized as alkaline soil (Table 14). The low soil acidity level is located in low land areas, in driest areas. The result implies that almost half of the study area was vulnerable to chemical land degradation. However, no area in the choke was affected by strong soil acidity. The key informant participants reported that the application of lime on the cropland has been increasing in the last 15 years, due to the increasing problem of soil acidity, mainly in the heavily cultivated middle and upper part of the sub-basin. Nevertheless, most farmers do not use lime to reclaim acid soil due to the scarcity of lime supply.

Table 14: The status of soil acidity in in Choke Mountain

Soil PH	Area (Ha)	Percentage (%)	Level	Assigned value
5-5.5	78984.99	3.95	High	4
5.5-6.7	779651.85	38.99	Medium	3
6.7-7.3	1116387.86	55.83	Low	2
7.3-7.8	24595.33	1.23	Very low	1

The Status of Comprehensive Land Degradation in Choke Mountain

The comprehensive land degradation map for this study was generated by integrating biological, physical, and chemical indicators of land degradation. All parameter raster maps were resampled to a 30 × 30 m cell size and re-projected to UTM Zone 37°N, WGS 1984 datum. According to the pairwise comparison matrix (Table 15), biological indicators were the most influential contributors to comprehensive land degradation, followed by physical and chemical indicators. The consistency ratio of the weighted comparison was 0.08, which is acceptable since it is below the 0.10 threshold.Results indicate that approximately 25.5% of the watershed is classified as low degradation, while 37.15% is moderately degraded and 36.5% is highly degraded (Figure 14). The spatial pattern of degradation is uneven, with the most severely degraded areas located in the lower portions of the watershed. This pattern is attributed to factors such as steep slopes, continuous cultivation, rugged topography, population pressure, poor land management practices, and erratic rainfall.

Moderately degraded areas are mainly found in the middle elevation zones, which are characterized by relatively plain topography and lower vulnerability to soil erosion. These findings are supported by local land users, who reported that a combination of soil erosion, low vegetation cover, reduced soil organic matter, and soil acidity are key drivers of land degradation in the Choke Mountain watershed. Additionally, the communities noted that climate variability, unsustainable farming practices, poor grazing management, and declining soil quality have exacerbated both soil erosion and overall land degradation in the area.Overall, the combined degradation analysis revealed that more than 71% of the watershed is moderately to highly degraded, highlighting land degradation as a serious environmental and economic challenge in the Choke Mountain watershed.The result is comparable to Ewunetu et al. (2011) conducted in north Gojjam sub-basin and Omo-Gibe River Basin (Dagne et al., 2023), Ethiopian Highland and Semi-AridWatershed of Rajasthan, IndiaMalav et al.(2022).

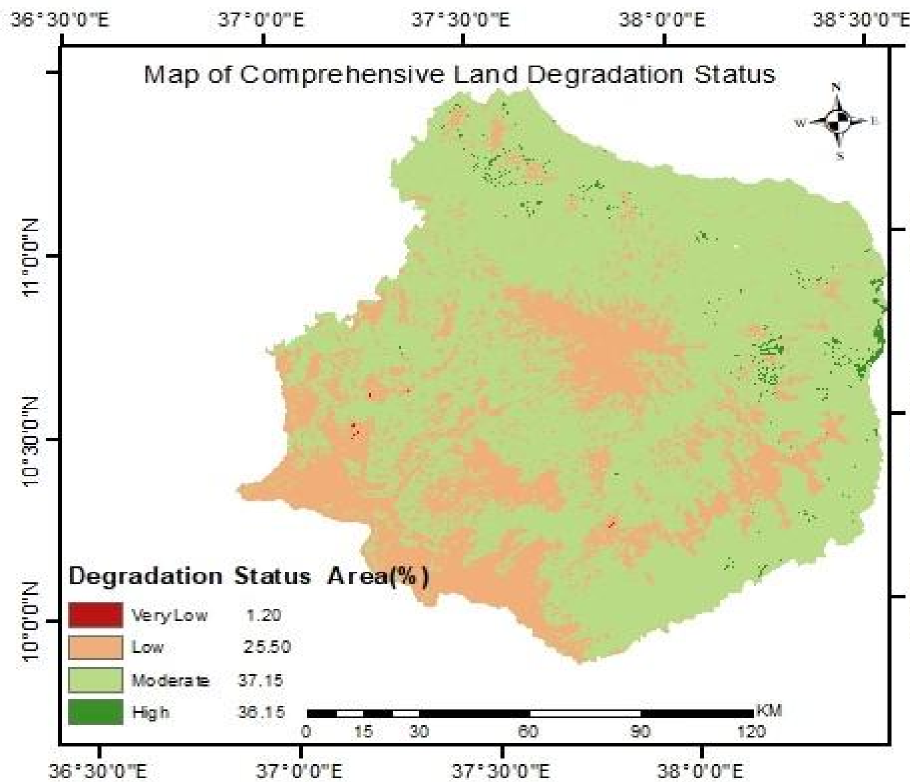

Fig.14: Comprehensive land degradation map of the north Gojjam sub-basin

Table 15: Pairwise comparison matrix of land degradation status in the north Gojjam sub-basin

Criteria	Biophysical degradation	Physical degradation	Chemical degradation	Criteria weighting
Biophysical degradation	1	3	7	68
Physical degradation	0.33	1	2	22
Chemical degradation	0.14	0.5	1	10

Conclusions and Policy Implications

Assessing land degradation is essential for developing evidence-based and efficient land management strategies. This study mapped and quantified multiple dimensions of land degradation in a typical highland setting of Ethiopia, the Choke Mountain watershed in the Upper Blue Nile Basin. Using standardized classification techniques in ArcGIS 10.5 and a hierarchical spatial MCA approach, several land degradation indicators were integrated into a single composite index. TheRUSLE model was applied to estimate soil loss rates by incorporating key factors such as topography, soil characteristics, rainfall, land cover, and local land management practices.

The RUSLE results indicate that the watershed loses approximately 44 t ha^{-1} yr^{-1} of topsoil on average. Moreover, about 45.3% of the Choke mountain watershed falls under high to very high soil loss risk. Biological land degradation emerged as the most severe type, while chemical (e.g., soil acidity) and physical degradation (e.g., compaction) were moderate in extent. Generally, more than 71% of the watershed was found to be moderately to highly degrade when combining all degradation indicators.

These findings underscore the urgent need for integrated land management strategies that combine structural, biological, and agronomic measures to restore and sustain environmental health and support local livelihoods. In particular:

- Soil fertility improvement: Application of lime to correct soil acidity and the use of organic fertilizers such as compost, manure, and mulching, are critical interventions.
- Erosion control: Adoption of agroforestry systems and economically viable, multi-purpose perennial crops should be prioritized to reduce soil erosion and rehabilitate degraded land.
- Stakeholder collaboration: Effective rehabilitation requires coordinated efforts among farmers, local communities, government agencies, and development partners to reduce ongoing degradation and enhance ecosystem resilience.

The study also reveals integrating GIS, remote sensing, and MCA techniques is a very vital for mapping and characterizing land degradation. Finally the study suggested that, land resources are dynamic and highly variable across regions due to diverse socioeconomic and biophysical conditions. This highlights the importance of continuous monitoring and regular engagement with local farmers to address emerging challenges and leverage opportunities for sustainable land management in the Choke mountain watershed and similar highland environments.

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