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ASSESSING THE IMPACT OF SOIL EROSION USING GEOSPATIAL APPROACH IN MINNA, NIGER STATE, NIGERIA

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ABSTRACT

Soil erosion remains a critical environmental issue, contributing significantly to landscape degradation, reduced soil fertility, and the deposition of unproductive materials on arable lands and waterways, often leading to the obstruction of rivers. This study employs Remote Sensing (RS) and Geographic Information Systems (GIS) techniques to model erosion and assess soil loss within the Minna catchment area, Niger State, Nigeria. The Revised Universal Soil Loss Equation (RUSLE) model was used for the estimation of soil loss, incorporating key factors such as rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and support practice (P) factors. The results of the soil loss analysis were classified into three categories: low (<10 t/ha/year), moderate (10–20 t/ha/year), and high (>20 t/ha/year). Spatial analysis revealed that 59% of the area experienced low soil loss, 14% moderate loss, and 26% high loss. The findings highlight that slope length, slope steepness, and rainfall intensity are the predominant drivers of critical soil loss within the catchment. A soil vulnerability map was generated, delineating zones of low, moderate, and high erosion risk. Overall, the study area exhibited a relatively low vulnerability; however, specific wards such as Sabon-Gari and Shatta showed a higher concentration of moderate risk zones. Additionally, scattered high-risk areas were identified in wards such as Limawa B Central, Limawa A, Minna C, Minna S, Nassarawa A, Nassarawa C, and Tudun Wada South. Based on these findings, the study recommends immediate intervention in moderate and high-risk zones to prevent further degradation. It also calls upon relevant authorities to expedite policy formulation and decision-making processes aimed at mitigating the impacts of soil erosion across the catchment.

KEY WORDS GIS, Remote Sensing, RULSE, Soil erosion, Soil Loss, Vulnerability.

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1. INTRODUCTION

Soil erosion is a major problem affecting many regions worldwide. Soil erosion is a stepwise process occurring when the collision of water or wind runoff removes soil particles, causing the soil to deteriorate (Abdulkadir et al., 2019). it is an environmental problem that is affecting the quality of soil and the environmental condition of areas globally (Babatunde *et al.,* 2016; Nwakwasi, 2018). The process of soil erosion involves the falling off and transport of soil particles by wind, water, or other agents, leading to the loss of fertile topsoil, degradation of the quality of land, and downstream sedimentation in water bodies (Adediji *et al.,* 2010). The problem may be so intense that the land may no longer fit for cultivation and must be forsaken, causing threats to agriculture and food production. Land degradation appears in different forms, the most common of which is soil erosion. It results from a combination of natural and human factors (Rosas and Gutierrez, 2019; Teng *et al.,* 2019; Bhattacharya *et al.,* 2020). Many agricultural civilizations have been reduced due to mismanagement of both land and natural resources, and the history of such civilizations still serves as a good reminder to protect our natural resources. Soil erosion is now a severe threat to the food security of Africa, Asia, and other developing countries (Shiferaw, 2011). Erosion is a serious challenge for productive agricultural land and for water quality concerns. Controlling the sediment is an integral part of any soil management system to improve water and soil quality.

The degree of soil erosion effectiveness is influenced by topography, precipitation, soil properties, land cover management, and soil conservation practices. A study conducted by (Negassa *et al.,* 2020) in the East Wollega Zone (western parts of Ethiopia) highlights that land use, land cover conversion, firewood collection and charcoal exploitation from forests for energy consumption, and overgrazing by livestock contribute to some of the major contributing factors to soil erosion. Therefore, estimating the soil erosion potential on agricultural lands is important so as to effectively implement preventive measures. In Minna, Niger state Nigeria, soil erosion poses threats to agricultural productivity, infrastructure stability, and overall environmental sustainability. it is a widespread phenomenon in Nigeria, as documented by many scholars. Most studies on erosion, especially gullies, come from the south-eastern states of Nigeria, which have a high population density, higher relief, steep slopes, deforestation, a humid tropical climate, and friable sandstones (Agim *et al.,* 2022). The Revised Universal Soil Loss Equation (RUSLE) stands as a widely acknowledged model (Maurya *et al.,* 2024) used to evaluate and forecast soil erosion rates in diverse landscapes. The Revised Universal Soil Loss Equation (RUSLE) model incorporates key factors that influence soil erosion, including rainfall erosivity, soil erodibility, slope length and steepness, cover management, and conservation practices. By quantifying these parameters and their interactions, the RUSLE model enables the estimation of soil loss rates and helps identify areas susceptible to erosion within a given landscape (Lal-Rindika et al., 2024). Previous studies, such as that of Woldemariam et al. (2023), have demonstrated the model's effectiveness in predicting soil loss and informing targeted erosion control strategies in comparable geographic settings. Despite this, there remains a scarcity of research focused specifically on the soil erosion dynamics in Minna, Niger State, highlighting the necessity for a detailed assessment using the RUSLE approach.

Conventional approaches to soil erosion assessment, which typically depend on field surveys and empirical models, are often labor-intensive, time-consuming, and susceptible to various inaccuracies (Calcagni et al., 2023). However, advancements in Geographic Information Systems (GIS) and Remote Sensing technologies have significantly broadened the scope for improving soil erosion evaluations through spatial analysis and modeling techniques. In response to the limited research on this subject within Minna, this foundational study aims to bridge the gap by analyzing soil erosion patterns, delineating high-risk erosion zones, and proposing site-specific soil conservation strategies tailored to the region's unique landscape (Sud et al., 2024). By integrating field observations, GIS-based spatial analysis, and the RUSLE model, the study seeks to contribute critical insights toward the sustainable management of soil erosion in Minna, Niger State, Nigeria.

2. MATERIAL AND METHOD

2.1. Study Area

Minna, the capital city of Niger State, is located in north-central Nigeria and spans an area of approximately 76.363 km². The study area lies between latitudes 9°32'30"N and 9°42'30"N and longitudes 6°20'00"E and 6°37'30"E. Geologically, the region is predominantly composed of gneiss and magnetite, underlain by an undifferentiated basement complex (Amadi et al., 2012). A prominent granite outcrop in the northeastern part of the city poses a natural barrier to urban expansion in that direction. Under the current political zoning structure, Minna covers an estimated 884 hectares. The city is situated about 145 kilometers by road from Abuja, Nigeria's Federal Capital Territory. Over time, the Minna metropolitan area has expanded to include surrounding settlements such as Bosso, Maitumbi, Dutsen Kura, Kpakungu, Shango, and Chanchaga. Urban development is primarily aligned along a central spine road, stretching approximately 20 kilometers from Chanchaga in the south to Maikunkele in the north. North of the railway tracks lies the city's high-density zones, including Sabon-Gari and the Main Market area, as illustrated in Figure 1.

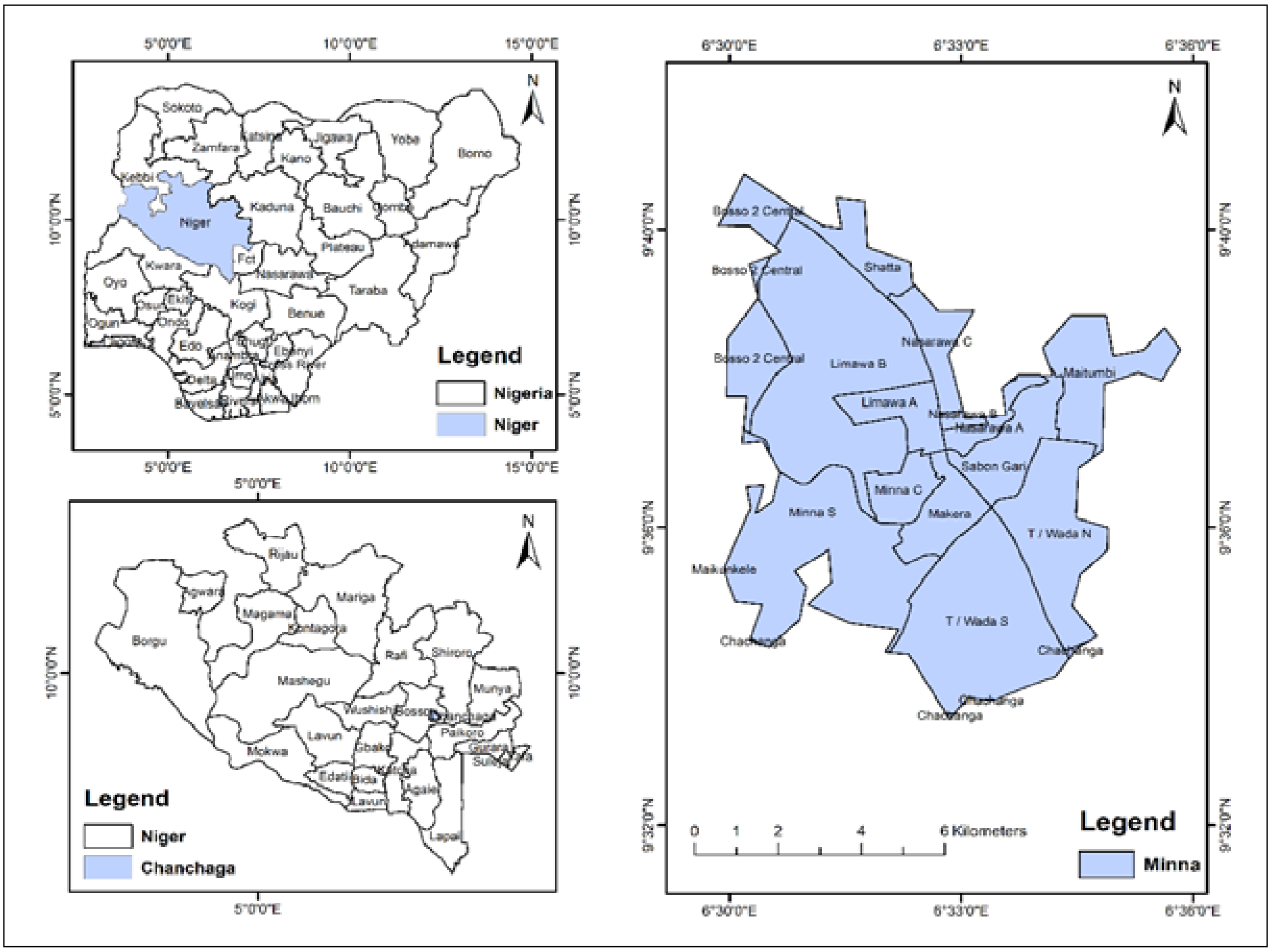

Figure 1.: Map of the study area: Top left, map of Nigeria showing Niger State, bottom left; map of Niger state depicting Chanchaga LGA; right side; map of Minna

3. METHOD

The study adopts a geospatial-based methodological design to assess the impact of soil erosion in Minna, Niger State, Nigeria. It involves the integration of satellite imagery, digital elevation models SRTMDEM, rainfall data, land use/land cover (LULC) maps, and soil characteristics to identify erosion-prone areas. Remote sensing techniques are used to detect changes in land cover and vegetation, while DEM analysis helps derive slope and drainage patterns that influence erosion intensity. These spatial layers are processed and analyzed in a GIS environment using RUSLE (Revised Universal Soil Loss Equation) model to estimate erosion risk levels. The final erosion impact map highlights zones of severe, moderate, and low erosion, providing critical insight for land management and soil conservation planning in the study area Figure 2, depicts the methodology framework of the research.

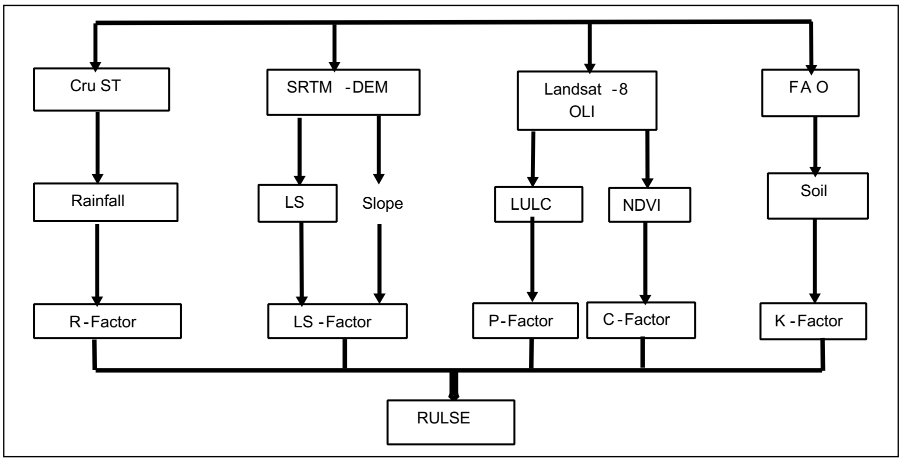

Figure 2: Methodology Flow Chart

3.1. Data Acquisition

The study used various geospatial datasets acquired from primary and secondary sources (Table 1). The dataset used for actualizing the RUSLE model comprises of rainfall, soil type, and Digital elevation model (DEM) and satellite images. the Landsat-8 Operational Land Imager (OLI) satellite image was download via the United state geological survey (USGA) having path 186/ row 053 was acquired on 27/10/2023 to extract information regarding land cover management and practices. Table 1, summarized the dataset used to carry out the research.

Table 1. Characteristics of The Dataset Used

Data	Spatial resolution/Scale	Sources	epochs
Soil	1:500,000	FAO	1998
Rainfall	0.5°×0.625°	Meera2	30 years
Dem	30m	USGS	2023
Administrative map	1:300,000	OSGOF	1977
Landsat	30m	USGS	2023

The multispectral image data underwent geometric correction to remove the effects of terrain displacement and to restore the correct geometry of the object's scene, shape and earth rotation (green *et al.,* 2014). This implies that the image's spatial orientation should corresponds to its actual position on the ground (Fawz *et al.,* 2006). Radiometric distortion correction was carried out by converting digital number (DN) to radiance values. Top atmospheric correction of all the bands of Landsat images is required to avoid the path of noise, this technique firstly convert the DN value to the atmospheric radiance using the following equation

$$\mathrm{L}\lambda = \frac{\mathrm{SR_k * DN}}{\mathrm{DN_{max}}} \quad 1$$

Where the saturated radiance of Kth band, DN is the digital number, and DNmax is the maximum possible value of a pixel.

A color band combination (Band-1, Band-2, Band-3, Band-4, Band-5, Band-6, and Band-7) was utilized to create a picture composite. The land use/land cover was generated by supervised classifications using the maximum likelihood classifier algorithm in ArcGIS 10.8 software. Land cover classes generated include aquatic bodies, vegetation (including agricultural land), built-up areas, and bare ground. The Normalized Difference Vegetation Index was created, and the vegetation's patches were classified into three categories based on the threshold of -1 to 0.1, 0.1 to 0.4, and 0.4 and higher. The first threshold identifies areas with no vegetation, the second identifies areas with shrubs and grasses, and the last identifies areas with dense vegetation.

3.2. Normalized Difference Vegetation Index

The NDVI works with an already defined formula stated below;

$$\mathrm{NDVI} = \frac{\mathrm{NIR\text{-}RED}}{\mathrm{NIR+RED}} \quad 2$$

Where Near infrared is band 5 and RED = band 4

The Shuttle Radar Topography Mission (SRTM) 1 Arc-Second DEM (30 m resolution) was acquired on 15/02/2023 to analyze the topographic influence on soil. Both Landsat image and SRTM DEM were collected from Earth Explorer (United States Geological Survey). The gridded rainfall data from Meera2, spatial resolution remains about the same (0.5°×0.625° (latitude & longitude) or approximately 50 km) with temporal resolution up to hourly. It uses the principles of retrospective analysis in refining earth data. Although, the datasets were reprocessed by Sorting and filtering, the telemetry data have passed through series of atmospheric reanalysis and adjustment before extraction (Baba *et al.,* 2024). The data downloaded was for the period of thirty (30) years (1992-2022) which cut across the Study area. Standardized soil profile data of the world that provides information about soil properties, especially sand, silt, clay content, and organic carbon for the analysis of soil erodibility was acquired on 22/06/2024 from Food and Agricultural Organization (FAO). Nigerian Administrative boundary shape-file was downloaded from DIVA-GIS.

3.3. Formation of RUSLE Model Factors

In order to achieve the stated objectives, the RUSLE model will be utilized with the following factors.

3.3.1. RAINFALL EROSIVITY (R FACTOR)

Rainfall erosivity is the first factor required in the model. The R factor is based on rainfall impact in the form of kinetic energy, and it also projects the rate and quantity of run off which is directly interconnected with a particular precipitation event (Wischmeier, *et al.,* 1978). According to Wischmeier and Smith, (1978), a time frame of 20–25 years is recommended for computing the annual average rainfall. As such, the monthly rainfall for the area of study was collected from Meera2 archive for a period of 30 years. The mean of the daily datasets for the 30-year Period were utilized to compute rainfall erosivity using the mean annual rainfall in line with the following formula:

$$R = 8.12 + (0.562 * \mathrm{P}) \quad 3$$

Where R is the rainfall erosivity factor and P is the mean annual rainfall (mm). The datasets were then processed in the ArcGIS 10.8 to produce continuous rainfall data for each grid cell with the aid of the spatial analyst tool.

3.3.2. SOIL ERODIBILITY (K FACTOR)

The K describes the sensitivity of soil properties (physical, chemical, and biological) to separation and movement by water following a storm Wischmeier and Smith (1978). The K factor was determined from the FAO soil map. Soil erodibility is determined by soil qualities such as texture, organic matter concentration, structure, and permeability (Renard *et al.,* 1997; Panagopoulos *et al.,* 2006; Chakraborty *et al.,* 2020). The research focuses on available soil texture, indicating the percentage of sand, silt, and clay, as well as organic matter, the most relevant soil qualities. (Tamene and Le 2015). The study used the formula below (Equation (4)) proposed by Zhang et al., (2019).

$$K\ Factor = fsand * fclay * forgC * fsilt * 0.1317 \quad 4$$

Where; Sand, clay, ForgC and silt are the outcome of the percentage values of the soil texture.

3.3.3. SLOPE LENGTH AND SLOPE STEEPNESS (LS FACTOR)

The LS factor incorporates two topographic factors: slope length (L) and slope steepness (S). Typically, as the slope length rises, so does the volume and rate of cumulative runoff. Similarly, when the land slope increases, so does the run-off velocity, resulting in widespread erosion (Ghosal and Das, 2020). The LS factor was then calculated by multiplying them in the map algebra of the spatial analyzer tool. It used the following formula:

$$LS= Power\ (FA * CS / 22.13,0.4) \times Power\ ((slope * 0.01745 / 0.09),1.4) \times 1.4 \quad 5$$

Where;

LS: Slope Length and Slope Steepness

FA: Flow Accumulation

CS: Cell Size

3.3.4. COVER MANAGEMENT PRACTICES (C FACTOR)

C-factor estimates the difference in predicted soil erosion due to variability in cropping and surface cover management (Tamene and Le 2015). The rate of soil erosion often varies within the different cover and crop management (yahya *et al*., 2020). C factor values range from 0 to 1, a value near zero witnesses a well-protected and dense vegetation, whereas values higher than 0.4 indicate the least covered surface and 1 denoting barren land highly vulnerable to rill erosion (Adediji *et al,* 2010).

$$C=\text{Expo}\ [-2* \quad \frac{\text{NDVI}}{\text{1-NDVI}} \quad 6$$

3.3.5. MANAGEMENT FACTOR (P FACTOR)

The final factor is management (P factor). This is the proportion of the loss of soil utilizing a certain support method to the equivalent loss from upwards and downslope tillage. (Renard et al., 1997). The management factor map was obtained from the land cover and weighed values assigned to the land uses from 0 to 1, where the highest value is given to areas with no conservation methods (open areas, water, bare and grasslands), while farmlands (agriculture area) are assigned various thresholds below 1 based on slope percentage, as recommended by Wischmeier and Smith (1978). After producing the R, C, P, LS, and K factor maps, the annual soil loss (A) was estimated using the mathematical equation.

$$A = R * K * LS * C * P \quad 7$$

Where;

A: Average annual soil loss in (tons/ha/year)

R: Rainfall erosivity factor (MJ.mm/ha/hour/year)

K: Soil erodibility factor (ton/ha/ h/MJ. mm/ha/hour/year

LS: Slope length and Flow accumulation factor (no dimension)

C: Cover and management factor (no dimension)

P: Management factor (no dimension)

4. RESULTS

This section covers results obtained from the study, in line with the study targets. It deals with the presentation and discussion of result obtained as outline in the research method.

4.1. The Rainfall Erosivity Factor (R-Factor)

It depicts the rainfall erosivity of catchment area ranges from 3308.2 to 3314.82 MJ.mm/ha/h/y. Having the eastern part including wards like Maitumbi, Tudun-Wada north and south, parts of Chanchaga and also few parts of Sabon-Gari and Wakera to be higher than the western part. (Figure 3. depicts the mean annual rainfall from Meera2 and its corresponding R-factors

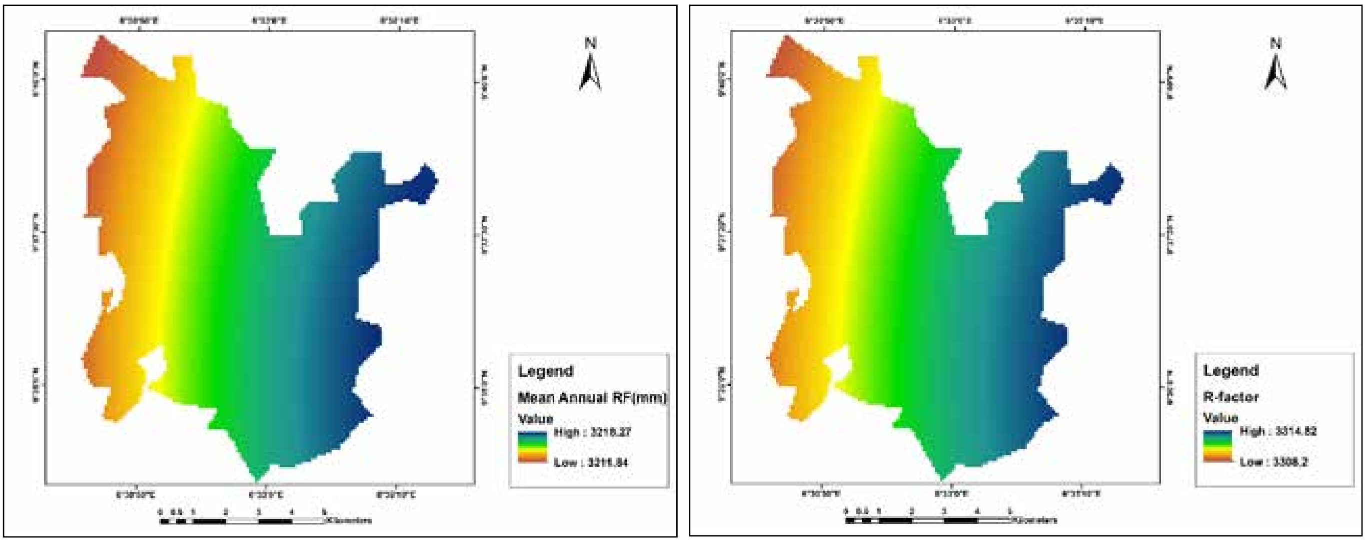

Figure 3: The right-hand side depicts Means Annual Rainfall Map of The Study Area, while to the Left is the Corresponding R-Factor Map

The rainfall erosivity is a key in RUSLE model, as calculated from the average annual total rainfall of 30 years from 3211.84 to 3218.27. MJ.mm/ha/h/year the catchment area. The mean annual rainfall was high toward the southeast, and low towards the northwest. Similarly, the amount of rainfall erosivity is determined using the rainfall map ranging from 3308.2 to 3314.82 MJ.mm/ha/h/year. Therefore, the eastern part of the study area receives relatively higher rainfall with high erosive power.

4.2. Soil erodibility and its K-factor map

The K factor Value determined from the digital soil map acquired by FAO (Food and Agriculture Organization of the World). The K-factor shows that the soil type covered all over catchment area is the Plinthic Luvisols (Lp) soil type with K-Factor value of 0.017113037 t/ha/yr. The levels are low throughout the catchment region and are attributable to the coarse soils which prefer water penetration rather than runoff. Figure 3.1 depicts the soil map generate from FAO and its K-factor map.

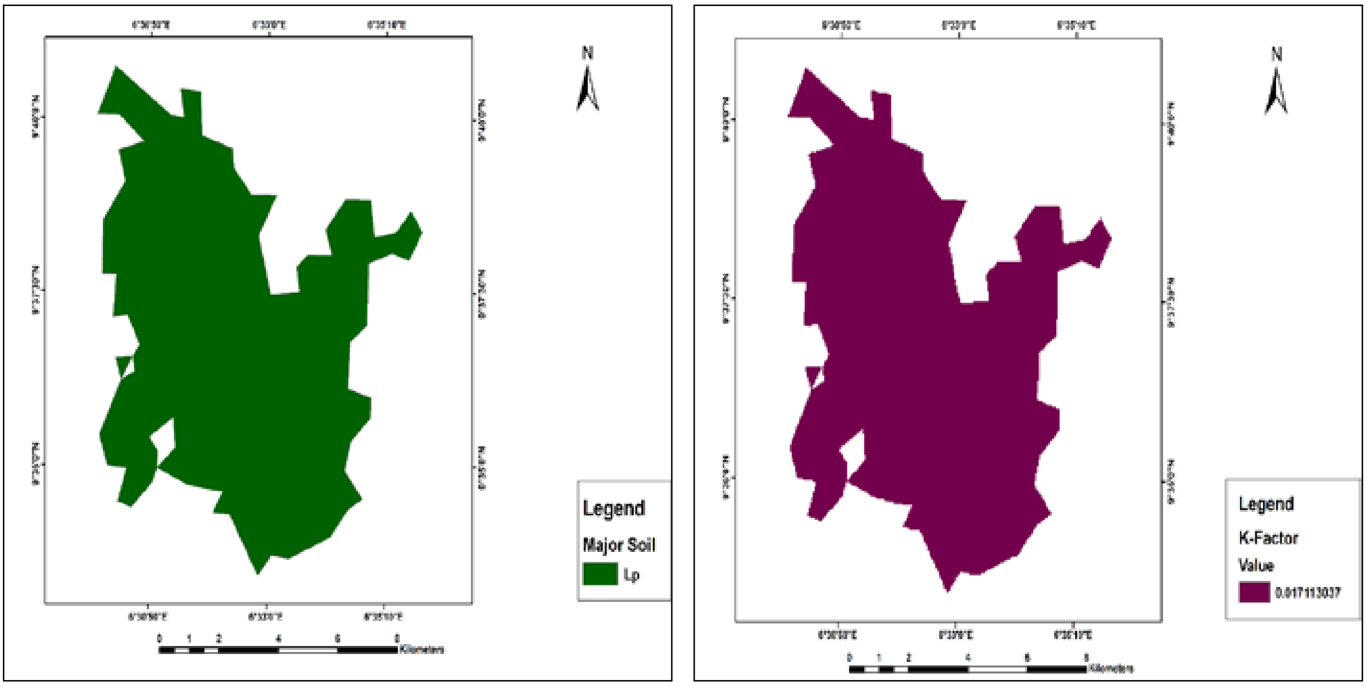

Figure 3.1: The soil map to the left and its K-factor map generated from FAO dataset to the right

4.3. The Slope Length (LS-Factor)

Different slope classes in the study area are shown in Figure (3.2). The LS factor in the catchment area ranging from 0 to 87.05, areas with high LS values are still areas with high slope values in slope degrees. The map was resampled to 30 m cell size. The erosivity of runoff increases with the velocity of the runoff water and steeper slopes produce high runoff velocities. Thus, in steeper slopes the water travels at a higher rate of speed and as a result, it increases its shear stress on the surface and its capability to transport more sediments.

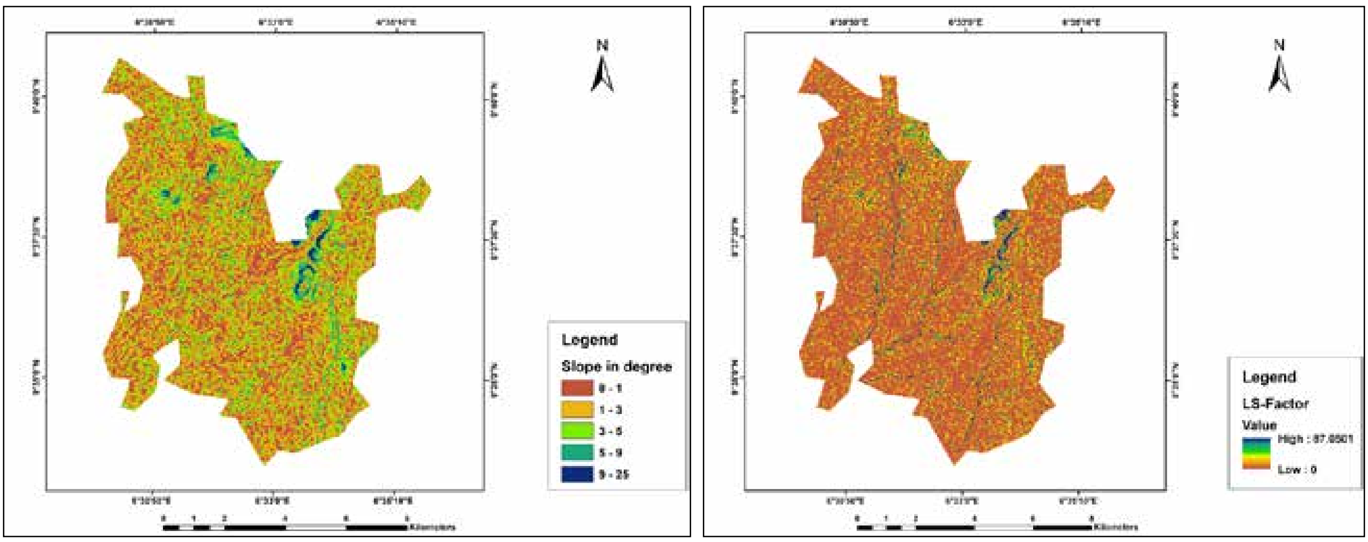

Figure 3.2: The Slope Map to the Righthand Side of the Map While L-S Factor Map is to the Left Side of the Map

4.4. The Cover Management Practices (C-Factor)

Vegetation forms have a positive NDVI value, which ranges between 0.1 and 0.7. The highest values are given to the densest vegetation cover. As shown in Figure 4.4a, NDVI values vary from 0.03 to 0.49. The C-factor map illustrates the way various land use patterns respond to erosion. The value of the C-factor across the entire study area in question is highly varied, ranging from 0.22 to 0.9. The C factor is an inverse of the NDVI. It tells us areas with high NDVI are areas with low vegetation cover, because these low areas are areas covered with built-up features. There is a low vegetation cover in pastures overgrazed by overstocking, sparse forests threatened by land clearing and cereal fields which are highly sensitive to all forms of erosion (water and wind). Figure 4.4 depicts NDVI values

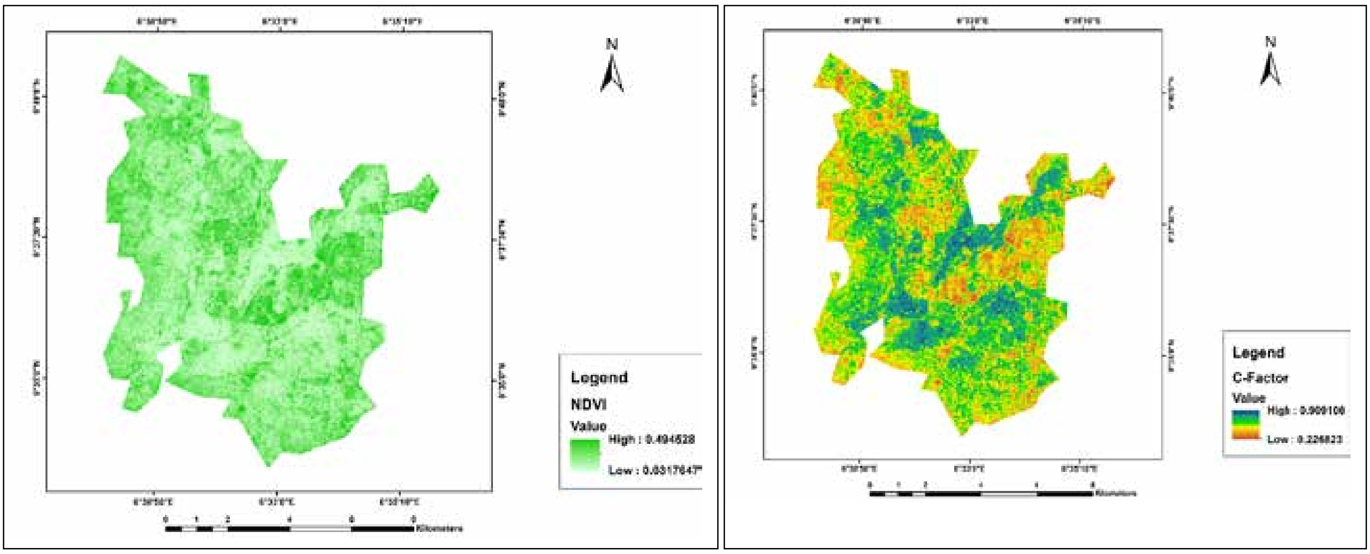

Figure 3.3. The right-hand side depicts the NDVI Map and to the left, C-Factor of the study Area

4.5. Management Factor (P-Factor)

The P factor ranges from 0 to 1. The smaller the value, the more effective the conservation strategy. The whole study area has not been treated with better permanent soil and water conservation methods. The P factor was taken into account based on land-use/land-cover, which was extracted from Landsat 8 image. To identify specific values for each management practice category, the image data were classified into four major land-use/land-cover categories (Fig. 4.5). After assigning P factor values for the land uses in the study area, the resulting map was converted to a grid map of 30 m cell size taking the P factors as values for the cells. Soil cover-preserving practices involve minimal cultivation, cover cropping, controlled grazing, contour planting, strip cropping, crop rotation, control structures, and diversions that safeguard soils from erosion by water by limiting the efficient slope length of a field.

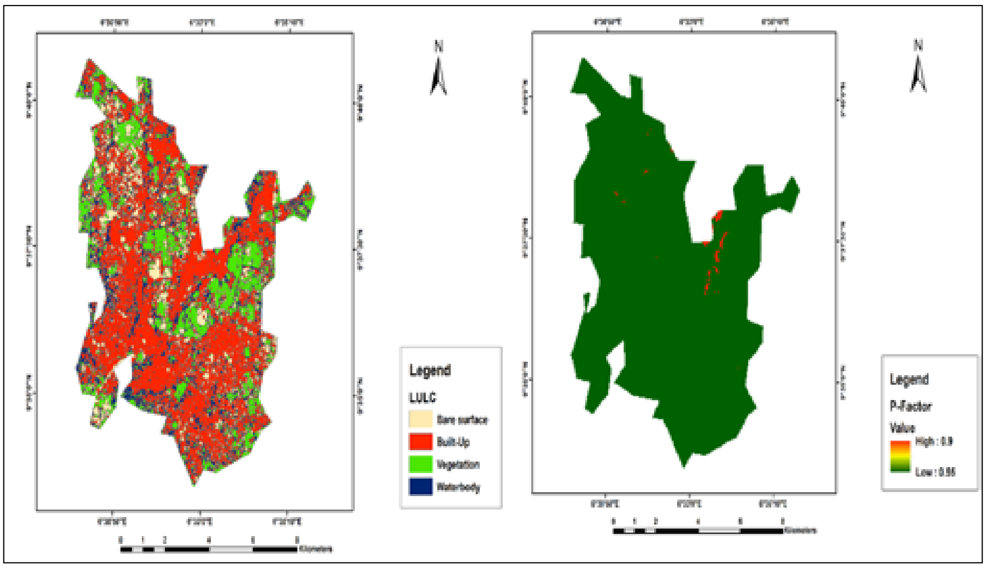

Figure 3.4 The right-hand side depicts LULCC Map and its P-Factor for the Study Area at the left side of the map

4.6. Soil Loss

The soil loss estimation using the RUSLE model was computed by multiplying the R-Factor, K-Factor, LS-Factor, C-Factor and P-Factor. The sensitivity analysis from the results reveals that the amount of annual average soil loss in Minna catchment, Chanchaga LGA, Niger Sate, Nigeria ranges from 0 to 1229.86 tons/ha/year. Figure 4. depicts the map showing soil loss in the study area.

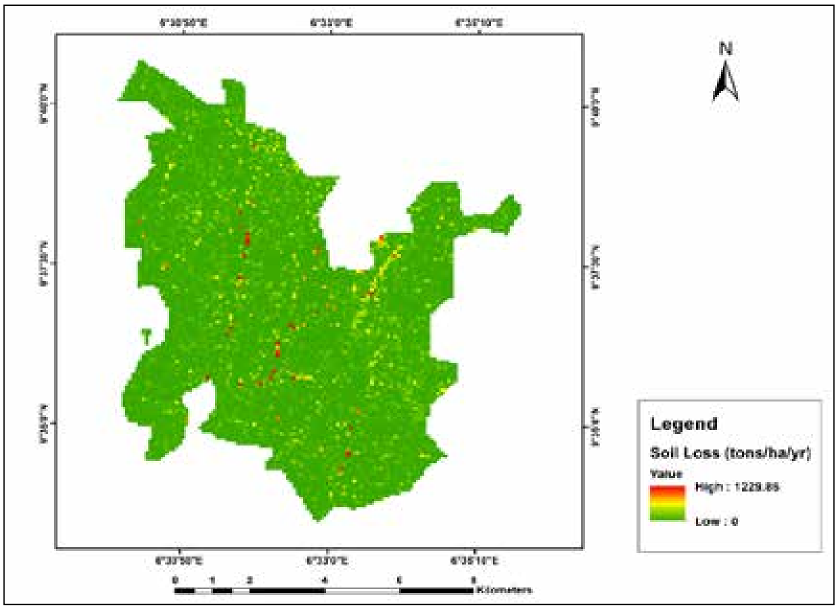

Figure 4.: Soil Loss map of the study area

5. MAPPING VULNERABILITY TO SOIL EROSION

Based on the result of the soil loss a vulnerability map was produced to depict the catchment area contains places that are prone to soil erosion. The breakdown indicates that roughly 59% of the region area has a low vulnerability of less than <10 tons/ha/year with an area coverage of 43.6092 km2, medium vulnerability of 10-20 tons/ha/year been 14% with an area coverage of 10.5105 km2, and high vulnerability of >20 tons/ha/year 26% coverage and area of 19.1764 km2. The areas having high vulnerability and extreme annual soil loss from the results merges with areas seen in high to medium rainfall precipitation, high slope degree and steepness and low vegetation cover. (Figure 5) shows the vulnerability map of Minna and environments.

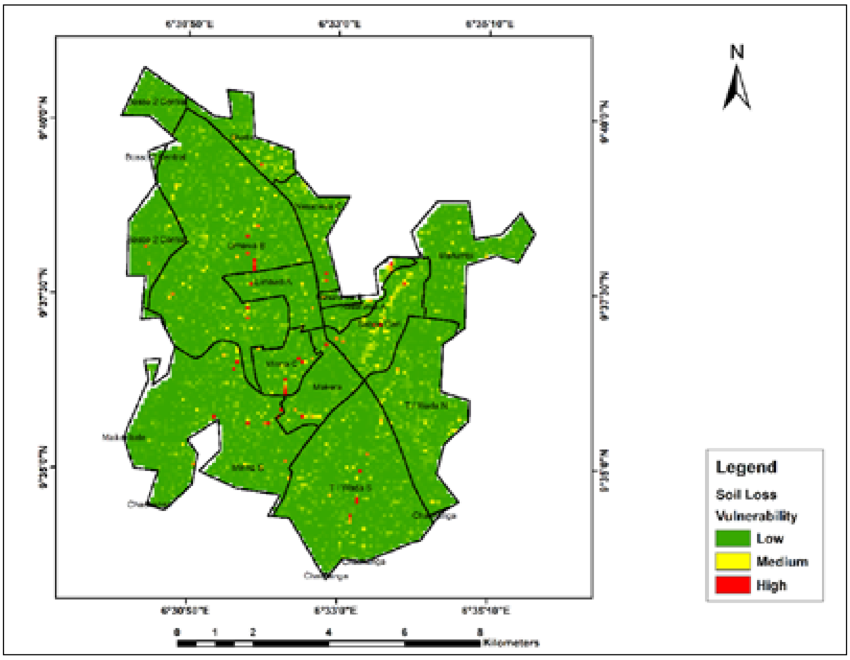

Figure 5: Soil erosion map indicating vulnerability areas

6. DISCUSSION

The phenomenon of soil degradation in Nigeria has seen an upsurge recently due to erosion, as pointed out by (Adeola, et al., 2019). The erosional impact is anticipated to grow due to climate fluctuations, as indicated by (Routschek et al., 2015: Zokaib et al., 2011), characterized by the rising intensity of rainfall, increased frequency, and the looming risk of disastrous consequences, particularly in West and East Africa regions according to (IPCC, 2013). Therefore, continuous and sustainable assessment, which is monitoring, and control of erosion constitute the fundamental requirement. According to (Ghosal et al., 2020), Remote Sensing (RS) and Geographic Information System (GIS) are recognized as crucial instruments for the assessment and management of soil erosion across a range of geographical scales.

The erosivity of rainfall, ranging between 3308.2 and 3314.82 MJ mm/ha/h/y in the catchment area, pertains to the coverage and proportion of the area, which spans approximately 39.28 Km2 (51.52%). These regions exhibit high erosivity, as illustrated in figure (3), and are predominantly situated in the eastern section of the catchment. Conversely, areas with low rain erosivity encompass an area of 36.97 Km2 (48.48%), primarily located in the western part of the catchment area. The dominant soil classification within the catchment area is identified as Plinthic Luvisols (LP), characterized by a K-Factor value of 0.017113037. This value was attained by excluding silt content from the sand and clay components to achieve precise soil property values. Analysis of slope length factors indicates that regions with significant flow accumulation occupy approximately 36.81 Km2 (49.38%), while areas with minimal flow accumulation cover about 37.73 Km2 (50.62%) of the catchment. High flow accumulation areas are concentrated within a slope degree range of (9-25) (figure 3.2), signifying steep terrains that facilitate soil erosion through accelerated runoff. A notable amount of the catchment area, approximately 61.53 km2 (80.72%), presents a low vegetation index, whereas about 14.70 Km2 (19.28%) exhibit a high vegetation index (Figure 3.4a). Study of the results illustrated in (Figure 3.4b) reveals that 39.73 Km2 (52.11%) are denoted by high vegetation cover, while 36.51 Km2 (47.89%) manifest low vegetation cover. Evaluation of management practices indicates that 1.26 Km2 (1.69%) adhere to high management standards, whereas the majority, encompassing 73.34 Km2 (98.31%), reflect low management practices.

Following the integration of all relevant layers using Equation 7, the RUSLE factors namely rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover management (C), and support practices (P) were converted into raster format for spatial analysis. The final results revealed that soil loss within the study area ranges from 0 to 1,229.86 t/ha/year. Based on this, the study categorized soil erosion risk into three classes: low (<10 t/ha/year), moderate (10–20 t/ha/year), and high (>20 t/ha/year), as shown in Figure 4 (Soil Loss Vulnerability Map). The average soil erosion rate across the study area was calculated to be 18.38 t/ha/year. The spatial distribution of erosion risk indicates that 43.60 km² (59%) of the catchment is under low erosion risk, 10.51 km² (14%) under moderate risk, and 19.17 km² (26%) under high erosion risk. Geographically, higher erosion rates are more concentrated in the central part of the catchment, with relatively fewer high-risk areas in the northern and southern regions. Figure 5 illustrates that approximately 73% (54.12 km²) of the area is susceptible to soil loss ranging from low to moderate levels (0–20 t/ha/year), while the remaining 26% (19.18 km²) is exposed to high erosion risk (>20 t/ha/year).

Several factors contribute to the observed pattern of soil degradation in the Minna catchment. These include the area's undulating and hilly terrain, the predominance of sandy loam soils which are particularly prone to erosion and high rainfall intensities. These physical characteristics are compounded by the absence of effective conservation measures and poor technical agricultural practices. Soil texture analysis further indicates high sand content (69.9%), moderate silt (10.5%), and relatively low levels of clay (19.5%) and organic carbon (0.73%). As noted by Saee et al. (2019), a higher percentage of silt can significantly increase soil erodibility, reinforcing the susceptibility of the region to erosion.

Furthermore, it is noticed that rainfall-runoff is the major energy source for detachment and transport of soil particles from the soil profile, thus increasing the erosive power and thereby making small rills converge to form large surface channels; gullies. Studies have shown that rainfall is the most important factor that is directly relevant to erosion studies in the tropics (Kavka et al., 2018). Rainfall intensity, duration of fall, drop size, frequency of fall, terminal velocity, annual total amount, kinetic energy among others are the rainfall characteristics that have the ability to loosen up soil structures and consequently detach earth materials from different surfaces. While runoff water carries the separated particles, where (Dimitrijević, 2023) states the result of the impact energy of raindrops causes the breakdown of aggregates. As a result, human populations have been displaced, ecosystem function has been degraded, and agricultural productivity and sustainability have decreased.

In addition, soil loss studies have shown that vegetation covering, particularly along with slope length and steepness, is a highly relevant component in managing soil loss (Abiol, 2019). This is due to the fact that vegetation cover has a direct effect on raindrops and soil particle detachment; dispersing raindrop energy before it reaches the soil (Ghosal, 2020) considerably reduces soil detachments and, as a result, erodibility. Nonetheless, the analysis revealed that the loss of soil is strongly impacted by LS and R variables. This is especially evident on the catchment's hilly and steep slopes, which exhibit a high soil loss risk despite high vegetation cover and NDVI values (Figure 3.3). In terms of managing soil erosion caused by LS in the Minna catchment, vegetation decreases the influence of soil loss to a low threshold (Figures 4 and 5), rather than absolute elimination. The findings are compatible with those of (Ugese et al., 2020), whom findings do not contradict those of (Adediji et al., 2010). Regarding Katsina state in Nigeria, they identified LS as the most significant and sensitive factor in their field of study. While (Gobin et al., 1999) stated that gully erosion in areas of Nsuuka in Southwestern Nigeria is influenced by all elements (infrastructure, geohydrology, topography, vegetation, and land use), they found that soil loss was greater on the escarpment than on plateau soils. In another vein, the places with great susceptibility and large annual soil loss in our results overlap with areas that receive extensive rainfall.

Results of soil loss assessment in Minna catchment revealed the fact that majority of the area is characterized by moderate or low erosion risk levels. The soil vulnerability map shows areas as characterized by low, moderate or high-level risk. Wards like Sabon-Gari is seen to have more of low risk, few moderate little of high risk at the northeast of the ward. Others wards like, Limawa B central, Limawa A, Minna C, Minna S, Nassarawa A, Nassarawa C, T/Wada south, are wards which high risk level is seen from the vulnerability map. Thus, the result of RUSLE model shows that it is more reliable compared to previous studies. However, due to its ease of use and low data requirements, RUSLE has also been recommended for usage, particularly in data-scarce locations like Africa. Additionally, RUSLE is advised for GIS compatibility across a range of scales, namely for use in areas with gently sloping terrain (Khassaf, and Al-Rammahi 2018). However, I recommend more research to fully comprehend the interactions between vegetation, precipitation, and soil loss as well as to find practical management techniques, particularly in areas with hills and steep slopes. Further research is advised to have a better knowledge of erosion in connection to various vegetation kinds, as well as infiltration rate. This will guide realistic and long-term management plans for controlling erosion in Nigeria.

7. CONCLUSION

The research employs a remote sensing and GIS-based approach using the Revised Universal Soil Loss Equation (RUSLE) model to assess the spatial distribution of annual soil erosion in the Minna catchment area, Niger State, Nigeria. This model integrates key erosion-influencing factors including rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), vegetation cover (C), and conservation practices (P). The study revealed an average annual soil loss of 18.38 tons/ha/year, with values ranging up to 1229.86 tons/ha/year in highly vulnerable zones. These findings highlight the catchment’s high erosion risk, which is largely driven by steep topography, poor vegetation cover, and inadequate conservation efforts. The analysis further identifies the significant role of topographical and climatic conditions in accelerating soil erosion. Irregular rainfall patterns, storm events, and the presence of soft rock formations contribute to the instability of the terrain. The low level of conservation practices, particularly on sloped land and exposed soils, exacerbates the erosion problem. Despite the low inherent erodibility of soils in the area, the lack of protective measures magnifies the impact of natural forces. The model thus serves as a critical tool for identifying erosion hotspots and prioritizing them for immediate intervention.

To mitigate erosion, the study advocates for a combination of soil conservation techniques, particularly in slope-prone areas. These include improved vegetation cover through the cultivation of species such as plantain, banana, and erosion-resistant grasses like Eulaliopsis binata, Neyraudia reynaudiana, and Cymbopogon microtheca. It also emphasizes the importance of regulating human activities such as waste disposal along riverbanks and restricting unapproved engineering structures in waterways. By promoting legal enforcement and public awareness, the proposed strategy offers a practical and replicable model for sustainable land and water resource management in erosion-prone, data-scarce regions.

8. REFERENCES

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Notes