



Erosion risk mapping of Anambra State in southeastern Nigeria: soil loss estimation by RUSLE model and geoinformatics

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Abstract

Soil erosion is a life-threatening hazard ravaging and displacing many communities in Anambra State, Nigeria. Most erosion studies in this region have been based on geological and geotechnical analyses of soils from gullies. In this paper, the soil erosion risk of Anambra State was evaluated using the Revised Universal Soil Loss Equation (RUSLE) and geoinformatics, to estimate the rate of soil loss and identify vulnerable erosion zones. The RUSLE model was based on five erosion factors (rainfall erosivity (R), soil erodibility (K), topography (LS), vegetation cover (C), and anti-erosion practices (P)). The R -factor ranged from 460.51 to 582.08 MJ/mm/ha⁻¹ h⁻¹ year⁻¹ whereas the K -factor ranged from 0.100 to 0.310 t/h/MJ⁻¹/mm⁻¹. Low–moderate LS -factor values dominated the northern and western portions of the State. However, moderate–high LS -factor scores dominated the eastern and southern portions. The C -factor varied from 0 (in areas covered by water bodies) to 1 (for barren lands). The P -factor ranged from 0.5–1. These five factors were integrated to generate soil loss rates across Anambra. The average annual soil loss ranged from 0 to over 6 t/ha⁻¹ year⁻¹. The soil loss results showed that about 5% (242.2 km²), 25% (1211 km²), 30% (1453.2 km²), and 40% (1937.6 km²) of the total area have very low, low, medium, and high erosion risks, respectively. The northern and western portions of the State were characterized by very low, low, and moderate soil loss. However, the eastern and southern portions were characterized by high soil loss rate. It was indicated that LS , K , and R are the most important soil loss factors in Anambra.

Keywords Erosion risk · GIS and remote sensing · RUSLE · Soil erosion susceptibility · Soil loss estimation

Introduction

Land resources are one of the most significant natural resources which sustain vegetation and human existence. Continuous loss of topsoil in large volumes via erosion has been considered an utmost threat to the world's soil resources (Kadam et al. 2019). Soil erosion by gully erosion is a life-threatening hazard ravaging and displacing many communities in southeastern Nigeria. Yearly, lots of lands, residential and commercial apartments, crops, and other valuable assets worth millions of dollars are lost to this menace. Because it is almost impossible to stop soil erosion in any region, mitigation and preventive measures are

usually adopted to reduce its impacts on human lives, natural assets, built assets, and wildlife. However, to ensure effective soil conservation, detailed knowledge and understanding of soil erosion causative factors and processes (Morgan 2005; Egbueri et al. 2021) and the spatial distribution of critical areas must be established. Such a strategy also considers that the several factors and processes that influence the erosion of soils vary from place to place.

Generally, soil erosion and the development of gullies are influenced and controlled by such factors as lithology or soil type, soil engineering properties, land-use/land cover, topography, slope, rainfall, amount and energy of surface runoffs, infiltration capacity, soil organic content, geological structures, groundwater distribution, landform, surface drainage pattern and distribution, and anthropogenic inputs (Morgan 2005; Nebeokike et al. 2020). Traditional methods for exploring the potential of a soil to erode include; geological, geotechnical, hydrogeological, and geophysical processes, which require skilled human resources. Moreover, these methods are often costly, energy-sapping, and

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time-consuming. Nevertheless, modern techniques, such as geospatial technology, are quite handy, less expensive, and cover a larger area while exploring soil erodibility and soil erosion risks. Numerical modeling, geographic information system (GIS), and remote sensing approaches have been successfully integrated and used by different researchers for different soil erosion studies (Morgan 2005; Marzloff and Poesen 2009; Wijesundara et al. 2018; Halefom and Teshome 2018; Kadam et al. 2019; Nitheshnirmal et al. 2019; Annayat and Sil 2020a, 2020b; Egbueri and Igwe 2021). Measuring erosion rates and mapping out vulnerable erosion areas are important and essential for prioritizing soil conservation measures.

In recent times, using empirical models coupled with geospatial techniques, soil loss estimation has been a promising research topic (Djoukbalala et al. 2018), that cuts across different scientific fields. Estimating the rate at which soils and sediments are lost from erosion-prone areas is paramount to designing and developing an effective mitigation measure. Empirical models such as soil loss estimator for southern Africa (SLEMSA), water erosion prediction project (WEPP), Griffith university erosion sedimentation system (GUESS), and wind erosion prediction equation (WEPE) have been proposed for the prediction of soil/sediment loss in different areas (Morgan 2005). Some other models, including the modified universal soil loss equation (MUSLE); sediment production rate (SPR); Limburg soil erosion model (LISEM); revised Morgan, Morgan, and Finney model (RMMF); and European soil loss erosion model (EUROSEM), have also been utilized (Morgan 2005). Over the years, it appears that the most widely used models for sediment loss estimation are the universal soil loss equation (USLE) and revised universal soil loss (RUSLE) (Wischmeier and Smith 1978; Renard et al. 1997; Morgan 2005). This is partly because the both have minimal computational procedures and are easily applicable to different regions of the world, unlike some others that are region-specific. Some other advantages of USLE or RUSLE over the other models include (1) the required input parameters could be acquired easily; (2) it comprehensively considers all the input parameters (factors); (3) it has the ability to provide information regarding regional soil erosion prediction; (4) it is highly compatible with GIS; (5) it has the ability to show the heterogeneity of soil erosion across a given region; and (6) it has strong practicability when compared with other physical models (Huang et al. 2020).

The USLE and RUSLE models are based on defining the most important erosion causative factors and, through observation, measurement, experiment, and statistical techniques, relating them to soil erosion (Morgan 2005). In other words, these empirical models consider distinct parameters (factors) that can depict how fast or slow a soil can be lost to erosion. The two models generally consider erodibility factor of

the soil (K), erosivity of rainfall (R), slope length (L , in meters), slope angle (S , in percent), vegetation or cultivation parameter (C), and conservative-management-protection parameter (P) (Wischmeier and Smith 1978; Renard et al. 1997; Morgan 2005; Youe-Qing et al. 2008; Owusu 2012; Dutta et al. 2015; Chadli 2016; Gashaw et al. 2017; Kayet et al. 2018; Das et al. 2018; Djoukbalala et al. 2018; Wijesundara et al. 2018; Koirala et al. 2019). Interestingly, soil erosion in areas with similar or different land-use patterns has been successfully assessed using the RUSLE model (Gashaw et al. 2017).

Although many gully erosion studies have been carried out in southeastern Nigeria, most of them are based on qualitative methods, describing the geology and index engineering properties of erodible soils (Egboka and Okpoko 1984; Igwe and Egbueri 2018; Egboka and Nwankwor 1985; Egbueri and Igwe 2020; Hudec et al. 2006; Akpan et al. 2009; Nwozor 2010; Igwe 2012; Chikwelu and Ogbuagu 2014; Okoyeh et al. 2014; Nebeokike et al. 2020; Obiadi et al. 2014). In other words, most erosion studies in Anambra State have been based on small-scale geological and geotechnical analyses of soils from gullies at various localities across the State. From literature review, it was observed that works related to erosion vulnerability/risk mapping research in the region using USLE or RUSLE are scarce, and there is an imperative need to carry out a larger scale research to show the rate of soil loss across the entire Anambra State. Interestingly, the use of RUSLE and geoinformatics would provide such a large-scale coverage. Therefore, this paper aims to integrate the RUSLE model and geoinformatics for the estimation of soil loss rates in Anambra State, Nigeria. The specific objectives are to (1) analyze the spatial distribution and interrelationships of the five RUSLE factors (R , K , LS , C , and P) in Anambra State; (2) quantitatively assess and predict regional soil erosion in the State; (3) determine the most influential RUSLE model erosion factors in the State; and (4) develop spatial erosion vulnerability maps for the State. This study gives special attention to Anambra State because it has the greatest number of gully erosion cases (sites) amongst the five southeastern states of Nigeria (Igbokwe et al. 2008; Egbueri and Igwe 2020). It is hoped that this paper will provide important information to urban/rural community planners, engineers, well-meaning citizens, and environmentalists towards identifying critical erosion zones that need urgent mitigation attention. Ultimately, this study could assist in preventing, monitoring, managing, and mitigating erosion hazards.

Materials and methods

Study area description

Anambra State is located in the southeastern part of Nigeria and found between latitudes $05^{\circ}40'N$ – $6^{\circ}50'N$ and longitudes $06^{\circ}30'E$ – $07^{\circ}20'E$ (Fig. 1). Having a land area of

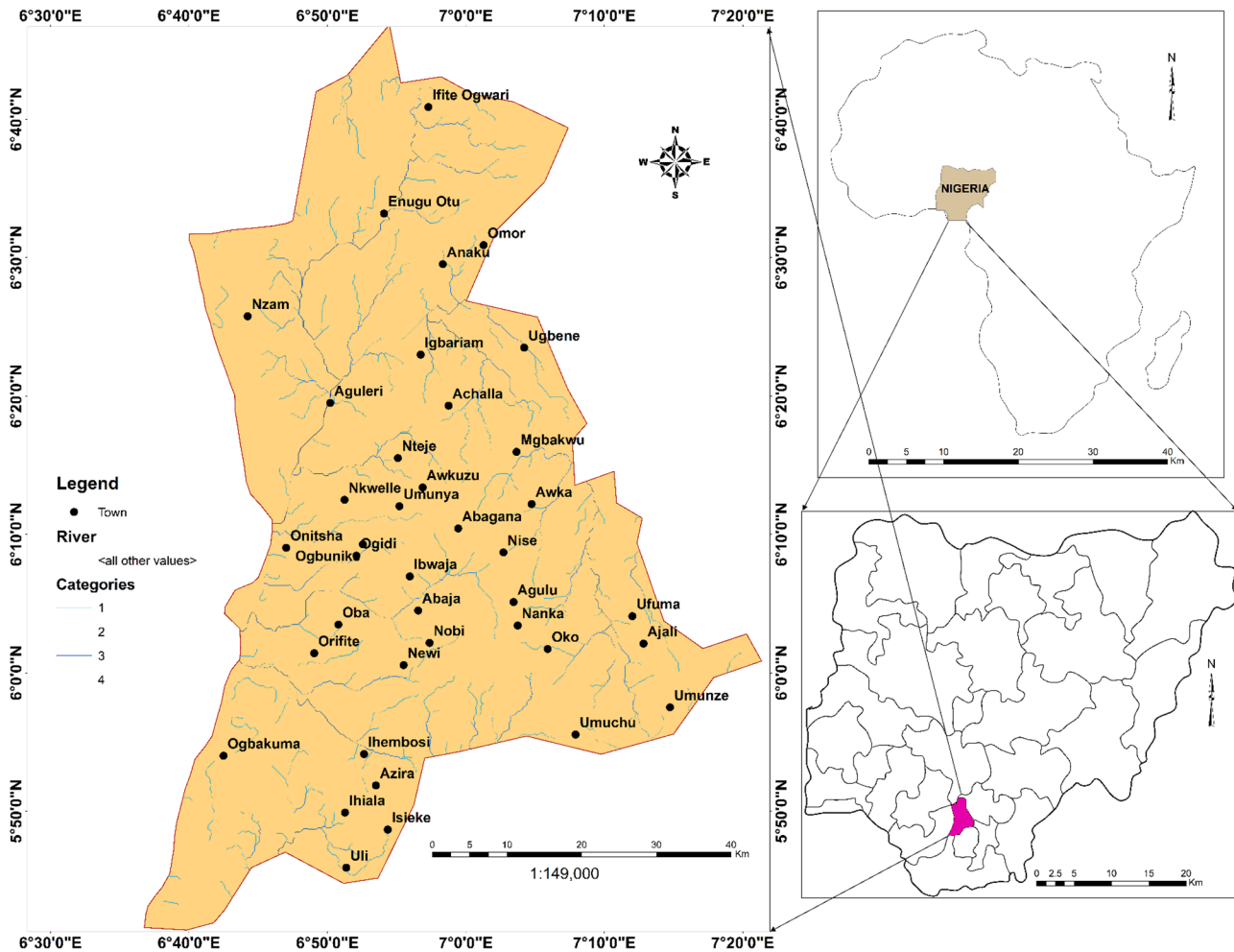


Fig. 1 Maps showing the drainage patterns and location of Anambra State in Nigeria and Nigeria in Africa

over 4500 km², the human population residing in Anambra has been estimated to be about 4,182,022 (Ejikeme et al. 2017). The State is well-known to have tropical climate. Two distinct climatic seasons, dry and wet, are peculiar to the study area. While the wet season spans around April to October, the dry season sets in from around November to March. The average annual rainfall of about 2000 mm is known to characterize Anambra State (Igwe and Egbueri 2018). The average annual humidity across the State ranges between 65 and 80% and an average temperature of about 26 °C. With respect to vegetation cover, the State is typical of a tropical rainforest belt. However, the vegetation has been altered due to anthropogenic activities such as industry, urbanization, agriculture, and unregulated deforestation. The topographic outlook is mainly undulating, with the average elevation ranging between 110 and 116 m. The topography seems to be controlled by geology. The State is drained by several surface water networks, all

tributaries to the larger Niger River in the western portion (Fig. 2). The main drainage networks (rivers) found in the State include the Niger River, Mamu/Ezu River, Omambala River, Ulasu River, and Idemili River.

The geologic map of Anambra State is shown in Fig. 2. The State is underlain mainly by young sedimentary deposits of the Niger Delta basin (Nwajide 2013). In the eastern and northeastern parts are deposits of the Imo Formation (age range: Paleocene to Early Eocene), whereas the central and southern parts are mainly of the Nanka Formation (age range: Eocene to Early Oligocene). The Imo Formation has more mudrocks with few unconsolidated sand units referred to as the Ebenebe Member. Meanwhile, the Nanka Formation constitutes abundant friable sand units and few mudrocks and ironstones. However, the western, southwestern, and northwestern parts of the State are underlain by alluvium and coastal plain sand deposits. The coastal plain deposit in the study area (Fig. 2) represents the Benin Formation (age range:

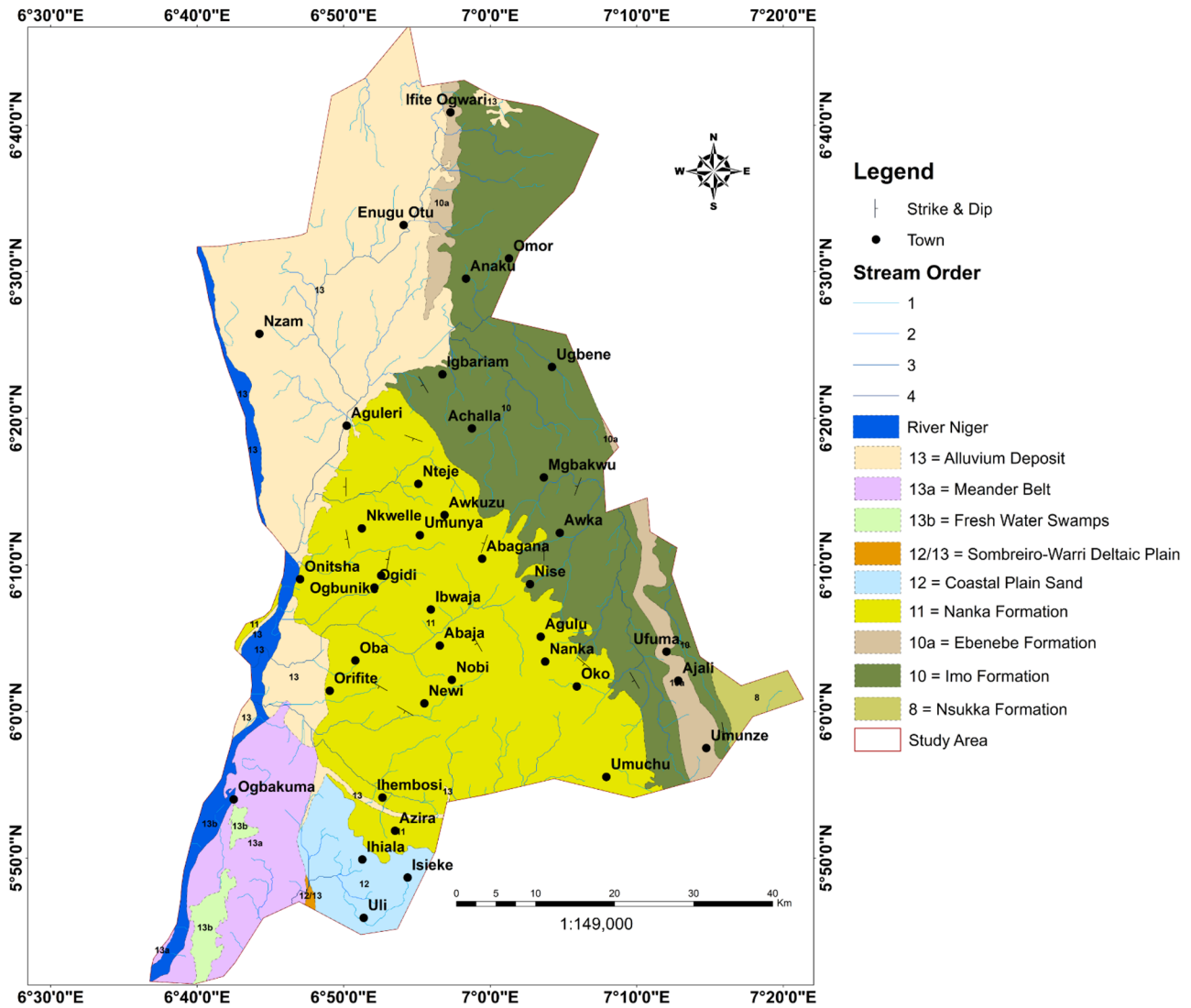


Fig. 2 Geologic map of Anambra State showing the predominant lithostratigraphic units

Oligocene to present). On the other hand, parts of the alluvium deposit around some towns, Orifite and Ihembosi (Fig. 2), are members of the Ogwashi Formation (age range: Oligocene to Miocene). Overall, all the geologic deposits are poorly consolidated (Egbueri et al. 2017; Nwajide 2013; Egbueri and Igwe 2020). Given such geologic conditions, soil erosion has been persistent in parts of the State. Sheet erosion, rill erosion, and gully erosion are the predominant types of erosion taking place in Anambra. Thus, there is incessant loss of agricultural, residential, and socioeconomic lands which poses threats to the economy, sustenance, and food security.

Geospatial datasets used

In the current study, various geospatial datasets were utilized, and their source(s) information is provided in Table 1.

Soil loss assessment using RUSLE

The RUSLE model (which presents the quantitative result of erosion risk in t/ha/year) was used for this study. The function used in the soil loss calculation is shown below (Eq. 1).

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

where *A* = estimated average soil loss in t/ha/year; *R* = erosivity of rainfall (MJ mm/ha/h/year); *K* = erodibility of soil (t ha h/ha/MJ/mm); *LS* = topography factor (dimensionless); *C* = vegetation cover factor (dimensionless); *P* = anti-erosion practices (dimensionless, ranging between 0 and 1) (Dutta et al. 2015; Chadli 2016; Gashaw et al. 2017; Kayet et al. 2018; Das et al. 2018; Djoukbalala et al. 2018; Wijesundara et al. 2018; Koirala et al. 2019).

Table 1 Information on the key datasets utilized for soil loss estimation based on RUSLE and geoinformatics

Dataset(s)	Source
DEM	Shuttle radar topographical mission digital elevation model (SRTM DEM). Cartosat-1 image was used for preparing the DEM
Slope/slope length, fill map, flow direction/flow height	Prepared from SRTM DEM data (30 m × 30 m resolution) obtained from US Geological Survey (USGS) website
Landuse/land cover	Prepared from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data downloaded from earthexplorer.usgs.gov (Path/row = 136/43; Bands used = 4, 3, and 2; Spatial resolution = 30 m; date = 20/06/2019). The satellite imagery was utilized through supervised classification of the false-color composite
Rainfall data	Prepared from rain-gauge data gathered from the Nigeria Meteorological Agency (NiMet) from years 2013 to 2018
Soil map	Prepared from the soil map of Nigeria obtained from World Soil Resources Office in cooperation with ORSTOM

Computation of the RUSLE factors

All the factors described in the RUSLE model were mapped in a raster GIS environment to obtain a pixel overview (30 m × 30 m spatial resolution) of the predicted average annual soil loss in Anambra State, southeastern Nigeria. Before compiling the RUSLE factors, geo-referencing of the raw datasets was done with geographical information system using the standard projections (Zone-32 N, UTM-WGS 85) and coordinate system. The study area boundary was delineated from digital imagery (SRTM DEM) using the spatial analyst tool of ArcGIS 10.5. The ArcGIS was also used for sub-setting the Landsat images and soil map. The methods for estimating the RUSLE factors are described below:

R-factor

In estimating the rate of soil erosion (by water) in an area, rainfall erosivity of that particular area is usually considered a major factor of the RUSLE model. The energy and impact of raindrops on the ease at which soil is disaggregated into movable sizes are represented as the *R*-factor of RUSLE (Djoukbala et al. 2018). It reflects the potential of rainfall to induce the erosion of soils (Dutta et al. 2015). In other words, this factor enumerates the influence of storms on soil and provides insight into the intensity and volume of surface runoff. In this study, *R*-factor is analyzed using the average annual rainfall of 5 years (2013 to 2018) as derived from the rain-gauge data was gathered from the Nigerian Meteorological Agency (NiMet) using the Thiessen polygon technique in ArcGIS 10.5 environment. Equation 2, as given by Choudhury and Nayak (2003), was used to obtain the *R*-factor.

$$R = 79 + 0.363Xa \tag{2}$$

where *R* = rain erosivity, and *Xa* = avg. annual precipitation (expressed in mm).

K-factor

The *K* of the RUSLE algorithm indicates how sensitive soil particles are to erosion by water. This parameter reflects the behavior of the soil under the compound (integrated) impact of raindrops, surface runoffs, and downward seepages through the soil. Generally, the *K*-factor is controlled by soil properties such as soil texture, penetrability, humus content, and presence of clays, with the texture being the most significant parameter (Das et al. 2018; Kayet et al. 2018). Because a soil’s resistance or vulnerability to water erosion is mainly dependent on its physical and compositional properties, the *K*-factor values vary with different soil types.

Various methods can determine the *K* component of the RUSLE. The Anambra soil map used for the *K* assessment was prepared from the Nigerian soil map (Table 1) in the current study. Classification of *K* for different soils is presented in Table 2.

LS-factor

The *LS* expresses the effect of the topographical configuration of an area on soil erosion by water. Both *L* and *S* variables are simply regarded as one topographic value in soil loss estimation. This factor depicts the important role slope plays in the detachment, transportation, and deposition of soil particles during erosion. Therefore, *LS* provides important information on the impact slope features on erosion

Table 2 Values of *K* (erodibility of soil) for different soil types

S/No	Soil type	<i>K</i> -factor values
1	Pale brown loamy soil (young soil)	0.120
2	Porous loamy soil (ferrallitic soil)	0.310
3	Red and brown soil (ferrallitic soil)	0.256
4	Reddish brown gravelly soil (hydromorphic soil)	0.100

rate (Djoukbalala et al. 2018). Studies have suggested that increasing slope length and angle directly and significantly influence soil erosion (Wischmeier and Smith 1978; Gashaw et al. 2017; Koirala et al. 2019). Alternatively stated, steeper and longer slopes allow for higher soil erosion rates due to an increase in runoff accumulation (Gashaw et al. 2017). However, slope steepness plays a higher role than slope length (Koirala et al. 2019). According to Koirala et al. (2019), soil loss due to slope configuration is influenced by vegetation cover and soil particle sizes. The present study produced the *LS* from SRTM DEM (30 m × 30 m resolution). The *LS* was reckoned by the formula presented in Eq. 3 (Moore and Burch 1986).

$$LS = (\text{Flow accumulation} \times \frac{\text{resolution}}{22.13})^{0.4} \times (\sin \text{ slope}/0.0896)^{1.3} \quad (3)$$

where “resolution” = grid cell size; “sin slope” = slope degree value in sine (Dutta et al. 2015). Table 3 shows the classification of the slope.

C-factor

The *C* component of the RUSLE is considered the second-most-important factor of soil erosion, as it represents the ratio to which the soil is covered or not covered by crops (Das et al. 2018; Dutta et al. 2015). Alternatively stated, the *C*-factor is indicative of the effect of cropping, vegetation, and other management practices on the rate of erosion (Koirala et al. 2019). The degree of soil loss in an area partly depends on the quantity and type of vegetation cover. Vegetation produces litter shields and inhibits the direct impact of rainfall on soil, thereby minimizing erosion (Igwe and Egbueri 2018; Djoukbalala et al. 2018).

Normalized Difference Vegetation Index (NDVI) has been widely used for estimating *C*-factor (Djoukbalala et al. 2018). Field-measured *C*-factor values or those obtained from guide boards and NDVI values derived from remotely sensed imageries have been used (Dutta et al. 2015; Djoukbalala et al. 2018). Equation 4 is used to evaluate the *C*-factor.

$$C - \text{factor} = 1.02 - 1.21 \times \text{NDVI} \quad (4)$$

Table 3 The value of “*m*” relative to each slope class used for slope map (Wischmeier and Smith 1978; Djoukbalala et al. 2018)

S/No	Slope steepness (%)	<i>m</i>
1	> 5	0.5
2	3–5	0.4
3	1–3	0.3
4	< 1	0.2

Currently, the *C*-factor values were assigned based on a simple assessment of land-use and vegetation cover rather than analysis of agricultural practices (Koirala et al. 2019; Kayet et al. 2018; Panagos et al. 2015). The land use/land cover (LULC) map, produced based on the step described by Koirala et al. (2019), was used for assessing the *C*. Afterwards, five types of LULC were extracted (Table 4), and for each of the identified land-use types, *C*-factor values (Table 4) were assigned. The *C* values ranged from 0 to ≈ 1. Traditionally, higher *C* values suggest that an area has no cover impact and soil loss rate like bare land, whereas lower *C* values indicate very strong cover impact, with little or no erosion (Ereñcin 2000; Koirala et al. 2019).

P-factor

The *P*-factor is related to anti-erosion exercises adopted to check soil (water) erosion. It reflects the impacts of conservation practices that reduce the volume and rate of soil erosion (Chadli 2016). Examples of soil conservation practices include cross-slope cultivation, contouring, strip-cropping, bonding, terracing measures, and check dam and configuration of surface drainage patterns, the velocity of runoff, and surface flow concentration (Renard et al. 1997; Chadli 2016; Wischmeier and Smith 1978; Gashaw et al. 2017; Kayet et al. 2018). The *P*-factor can also be obtained by collecting data from field observations (Gashaw et al. 2017).

According to Morgan (1986), the value of *P* is taken to be 1.0 when there are no specific values for soil conservation practices in an area. The *P*-factor for this study was based on Dutta et al. (2015). Maximum likelihood classifier was utilized for classifying the generated Landsat image (Fig. 3), with the cell pixels of each LULC class assigned *P*-factor values (Table 4) in accordance with recommendations in the US Department of Agriculture (USDA) Handbook (1981). The *P*-factor values vary from 0 to 1, based on anti-erosion techniques used in an area. *P*-factor equal to 0 signifies zones well protected from erosion, while *P*-factor equal to 1 indicates zones without any soil conservation practices (Koirala et al. 2019).

Table 4 *C*-factor and *P*-factor values used for RUSLE modeling

S/No	LULC classes	<i>C</i> -factor value	<i>P</i> -factor value
1	Barren land	1.0	1.0
2	Water body	0.0	1.0
3	Agricultural land	0.5	0.5
4	Settlement	0.7	0.7
5	Vegetation	0.8	0.8

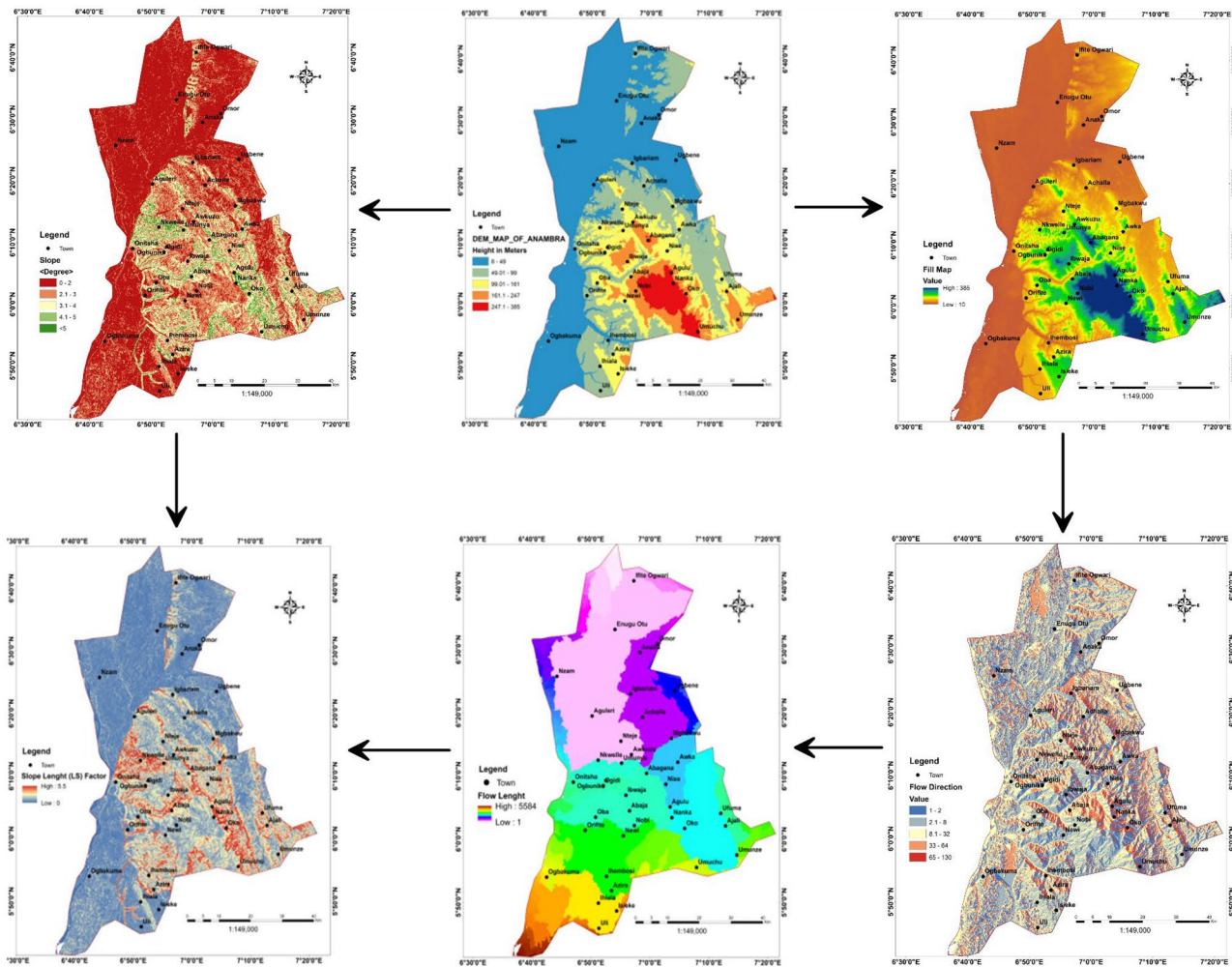


Fig. 3 Derivation of *LS* map. As indicated by the arrows, information regarding the DEM, slope, fill, flow direction, and flow length across Anambra State were integrated to generate the *LS* map

Results and discussion

Geospatial distribution of RUSLE factors and erosion assessment

R-factor

Five-year average annual rainfall data were used for the present study. It was estimated that the area receives a mean annual rainfall in the range of 1051–1385.9 mm (Fig. 4a). Spatially, it was noticed that the eastern and southern parts of the State experience higher rainfall intensity than the northern and western parts of the State (Fig. 4a). Studies have shown that higher rainfall induces high soil erosion (Cuomo and Della Sala 2013; Cuomo et al. 2016; Baumann et al. 2020; Huang et al. 2020). Based on field observation, the eastern and southern parts of the State experience more soil erosion and have more rills and gullies than the northern

and western parts with lower rainfall intensity. Nevertheless, the rainfall data were utilized in calculating the rain erosivity.

The *R*-factor values were observed to range between 460.51 and 582.08 MJ mm ha⁻¹ h⁻¹ year⁻¹ (Fig. 4b). Based on the information provided by Fig. 4b, it is seen that the *R*-factor showed spatial variations across the State. However, it is pertinent to note that the variation of the *R*-factor correlates with the average annual rainfall distribution. As *R*-factor is an index of average annual precipitation occurring in the area, both follow the same spatial pattern (Das et al. 2018). Hence, it was realized that the highest *R*-factor scores are found in the eastern and southern parts of the study area, whereas the lower scores were found in the northern and western parts of the State.

While the northern and western parts of the State have lower slopes and topography, the eastern and southern parts have higher slopes and topography with higher rainfall

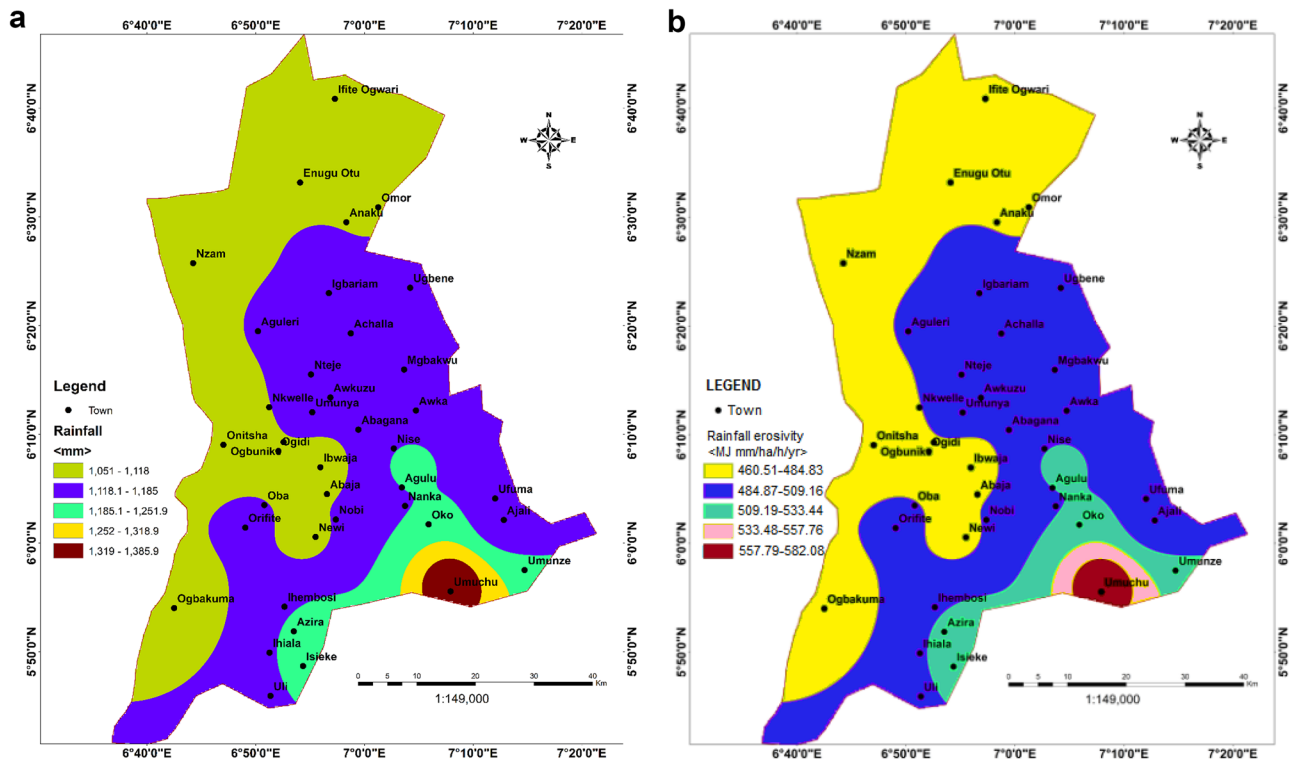


Fig. 4 **a** Rainfall distribution map of Anambra State showing areas with higher and lower rainfall intensities. **b** Rainfall erosivity map of Anambra State showing areas with higher erosivity and lower rainfall erosivity

erosivity (Fig. 4). A similar observation has been reported by other authors across the globe (Cuomo and Della Sala 2013; Das et al. 2018; Wijesundara et al. 2018). Das et al. (2018) reasoned that higher R -factor could be due to highlands and moderate-steep slope landscape. This could further be attributed to the fact that places situated on higher elevations are far more exposed to direct impacts of rainfall and runoff. The R -factor for this study indicates that the slopes and topography of the study area significantly control the erodibility of the soils (Egbueri and Igwe 2020).

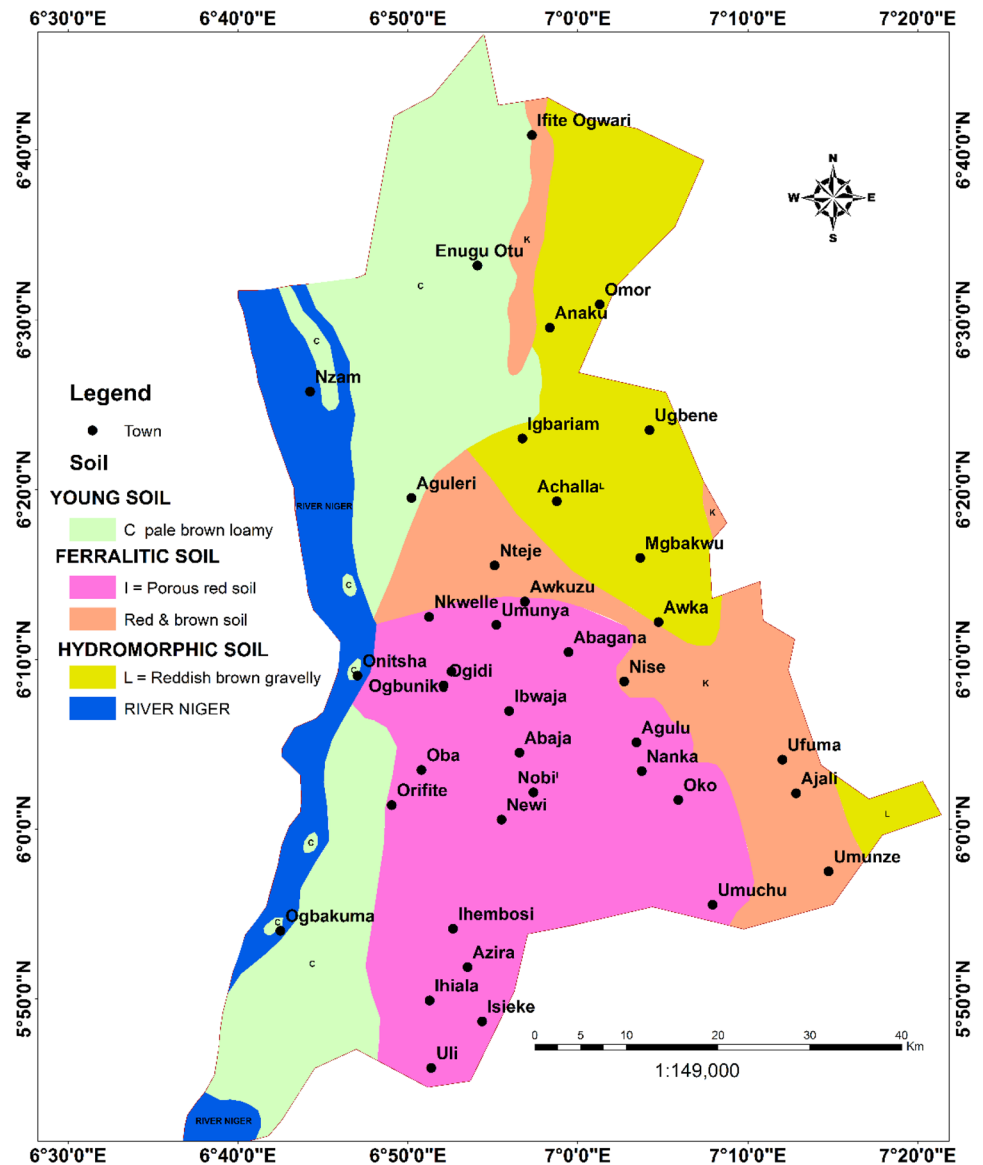
K-factor

The soil erodibility factor (K -factor) depicts the contributions of different soil types to water erosion. The spatial distribution of the K -factor reflects the dissimilarity in the rates at which different soils erode when other factors inducing erosion are considered constant (Das et al. 2018). A soil map of Anambra State was produced for this research (Fig. 5). Four major soil types (textures) were identified. It was realized that the northern and western portions of the State, characterized by lower R -factor values, are underlain by young, immature soils (pale brown loamy soils) and hydromorphic soils (reddish-brown gravelly soils). Alluvial and clayey deposits in the western part of the area are common

(bordering the Niger River and its distributaries). However, the eastern and southern portions of the study area, which have higher R -factor scores, are characterized by ferralitic (highly weathered and leached) soils (Fig. 5). Based on the four different soil types found in Anambra State, the K -factor scores were evaluated.

The K -factor was in the range of 0.100 to 0.310 $t h MJ^{-1} mm^{-1}$ (Table 2). It was also realized that the soils in the eastern and southern parts of the State have higher K -factor values than those underlying the northern and western portions. Studies have suggested that soils with high K -factor scores have higher erosion risk susceptibility and vice versa (Kumar and Kushwaha 2013; Dutta et al. 2015; Wijesundara et al. 2018). Therefore, it is evident that the eastern and southern portions of the State are more susceptible to water erosion than the other portions. The northern and western parts of the area are dominated by alluvial and gravelly soils, which seem to be more resistant to erosion when compared to ferralitic soils. Due to high infiltration in alluvial soils, the runoff is usually reduced. Similarly, gravelly soils tend to have a higher resistance to detachment due to their higher density. Previous erosion research conducted in the eastern and southern parts of the State showed that the soils are generally sandy, silty, loose, and readily erodible (Chikwelu and Ogbuagu 2014;

Fig. 5 Soil map of Anambra State showing the distribution of various soil types



Egboka and Nwankwor 1985; Okoyeh et al. 2014; Egboka and Okpoko 1984; Igwe 2012; Obiadi et al. 2014; Nwozor 2010; Igwe and Egbueri 2018). The higher susceptibility of the soils underlying the eastern and southern parts could also be attributed to the ease with which these soils form crusts, which induces high runoff volumes and velocities (Ganasri and Ramesh 2016).

LS-factor

The *LS* component was considered to express better the possible impact of topographic configuration on the erodibility of the soils in the study area. The *LS*-factor map is shown in Fig. 3. The parameters that were integrated to generate the *LS*-factor map include DEM, slope, fill, flow direction,

and flow length. There seem to be some interrelationships between these parameters in connection to soil erosion. First, the DEM shows the distribution of elevations, which is related to the slope. The DEM map shows that the study region has uneven (non-uniform) topography. Again, the DEM and slope map shown in Fig. 3 suggest that the southern and eastern parts have higher topography and slopes. The higher the slope, the higher the soil erosion tendency (Gashaw et al. 2017; Koirala et al. 2019; Huang et al. 2020). Further, the fill, flow direction, and flow length maps were also shown in Fig. 3. Accordingly, these maps were seen to correlate well with the DEM and slope map. It was observed that, while the fill increases, the flow direction and length increase (Fig. 3). The southern and eastern parts of the study area were seen to have higher fill and flow direction and

length. Thus, the higher the sediment fill and the higher the flow accumulation and flow length, the higher the rate of soil loss.

Based on the information represented in Fig. 3, it is seen that the northern and western portions of the State are dominated by low to moderate *LS*-factor values. In contrast, the eastern and southern portions are dominated by moderate to high *LS*-factor scores. The lower *LS*-factor values peculiar to the northern and western parts of the State are thought to be partly influenced by the Niger River watershed. The higher *LS*-factor peculiar to the eastern and southern parts of the study area is thought to be partly influenced by the nature of soils and lithology (mostly lateritic sand units) predominant in these regions. Furthermore, it seems that the northern and western parts are more characterized by even topography while the eastern and southern parts are more characterized by uneven (undulating) topographic configuration. The incessant rill and gully formation in the eastern and western parts are also believed to influence their undulating landscape. The variations in the slope steepness and length across the study area reflect a variation in the area's rate and amount of soil loss.

The results of the *LS*-factor derivation (Fig. 3) suggest that the eastern and southern portions of the current study area are more susceptible to erosion than the western and northern portions. This assertion agrees with the results of the *R*- and *K*-factors. The findings of this investigation seem to also agree with those of previous researchers. It has been reported that increasing slope length/steepness directly increases the *LS*-factor; thus, leading to higher erosion risk (Wischmeier and Smith 1978; Dutta et al. 2015; Gashaw et al. 2017; Das et al. 2018; Wijesundara et al. 2018; Koirala et al. 2019). Alternatively, soil erosion risk is higher in areas with steeper and longer slopes than in areas with gentle and shorter slopes. This could be attributed to the tendency of higher runoff accumulation and subsequent rapid soil loss from steeper and longer slopes (Koirala et al. 2019; Gashaw et al. 2017). However, Koirala et al. (2019) noted that slope steepness plays a higher role in soil loss than slope length.

C-factor

How far soils are exposed to the direct impact of rainfall and runoff significantly determines the tendency of the soils to erode. The more barren a region, the higher its soil erosion rate and amount. This is because vegetation cover (reflected as the *C*-factor) usually seems to slow down soil erosion by plant canopy structures and litter covers (Igwe and Egbueri 2018; Djoukbalala et al. 2018). Generally, the *C*-factor of the RUSLE model scales between 0 and 1. In the present study, the *C*-factor values ranged between 0 and 1. Studies (Ereñcin 2000; Koirala et al. 2019) have shown that lower *C*-factor scores indicate a strong cover impact (which implies a

reduction in soil loss/erosion) whereas higher *C*-factor scores indicate low cover impact (which implies an increment in soil loss rate and amount). The scores for the various LULC classes are shown in Table 4. The *C*-factor values varied from 0 for areas covered by water bodies (needing no vegetative protection) to 1 for barren lands (with no cover protection) (Ganasri and Ramash 2016; Wijesundara et al. 2018).

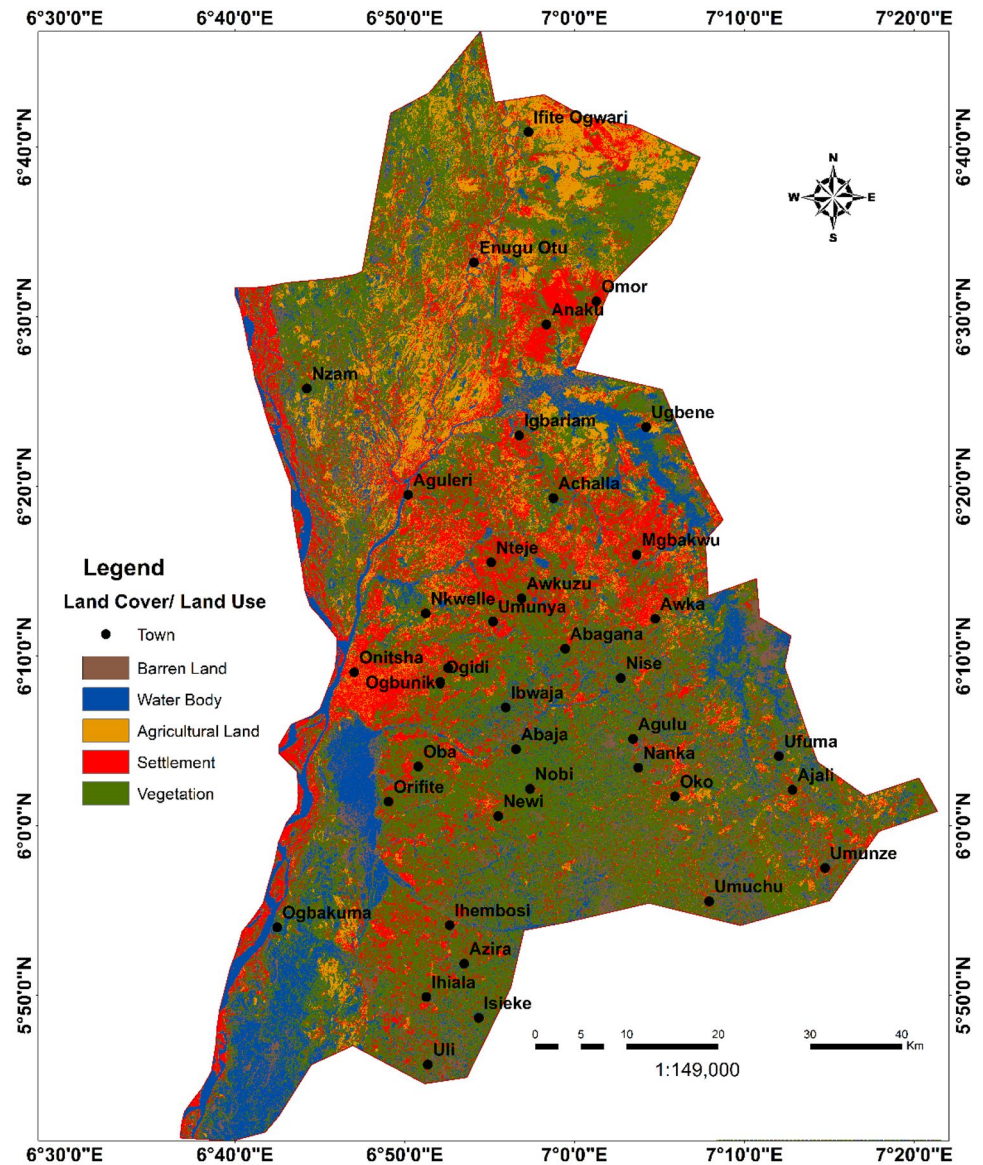
Figure 6 shows the geospatial LULC distribution of the study area. Five major LULC classes were identified in Anambra State. They include the areas covered by barren lands, water bodies, agricultural lands, settlements, and vegetation covers. It was observed that surface water bodies dominate the western and extreme eastern portions. Agricultural activities dominate the northern and southwestern parts. A more significant percentage (about 60%; 2906.4 km² out of 4844 km²) of the study area has vegetation covers, especially in the eastern and southern portions of the uneven (undulating) terrain. It is pertinent to note that the vegetation cover of the study area is sparse and typical of the distorted tropical rainforest. Thus, the vegetation cover seems not to have a significant impact on erosion control in the area. In other words, the vegetation in the area is a weak controller of soil erosion. The common vegetation and crops cultivated in the area include palm trees, shrubs, bamboo trees, grasses, cassava, yam, cocoyam, banana, plantain, and other annual crops.

P-factor

The *P*-factor reflects the degree of effectiveness of soil conservation practices established in an erosion-prone area. Traditionally, *P* values vary between 0 and 1 regarding the anti-erosion techniques utilized in an area. Areas well-protected from erosion forces usually have lower *P*-factor values while areas that are not well-protected from erosion (i.e., lacking effective soil conservation practices) are assigned higher *P*-factor values (Wijesundara et al. 2018; Ganasri and Ramesh 2016; Koirala et al. 2019). For this study, the *P* values for the 5 LULC classes are detailed in Table 4. Generally, Anambra State is characterized by high *P*-factor values (≥ 0.5), as effective soil/water erosion mitigation measures are deficient.

The *P*-factor scores for this study ranged from 0.5 to 1, with agricultural lands (where strip-cropping and terracing measures are implemented) considered to support erosion-check more than other LULC classes. Settlement was assigned a factor of 0.7, because some conservation practices (such as construction of surface drainage systems, runoff breakers, and local check dams) are in place. The vegetation class was assigned a factor of 0.8. This is because the vegetation is only believed to provide a weak support system in checking erosion. In some portions of the State, the most common vegetation used in mitigating soil erosion is bamboo trees.

Fig. 6 Map showing the distribution of the predominant land use/land cover (LULC) of Anambra State

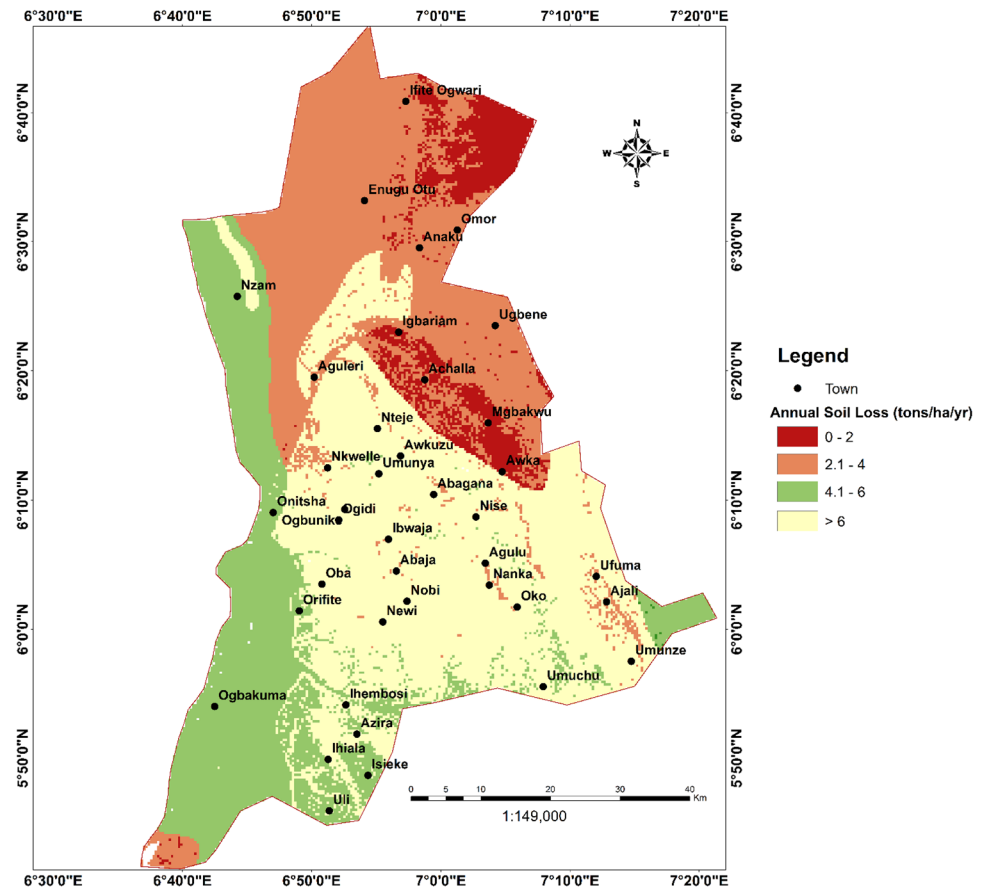


Erosion risk prediction by RUSLE model

The soil loss map of Anambra State has been produced using geospatial technology by multiplying the five RUSLE factors (Fig. 7). The current study utilized a modeling approach to develop the spatial analysis of the erosion risk across the Anambra State using remotely sensed imageries and the RUSLE algorithm. Though several erosion studies (at watershed and local scales) have been carried out across the State, it seems that this is the first time this study approach is utilized to assess its erosion risk. Weighted overlay analysis of the five factors was adopted in this study. Although this approach has some limitations, it provides several useful information for identifying priority areas to consider for soil erosion mitigation interventions (Koirala et al. 2019).

Different classification systems have been utilized in grouping average soil loss (*A*) values. For instance, Dabral et al. (2008) proposed five *A* classes based on Indian conditions as, slight ($A = 0\text{--}5 \text{ t/ha}^{-1} \text{ year}^{-1}$), moderate ($A = 5\text{--}10 \text{ t/ha}^{-1} \text{ year}^{-1}$), high ($A = 10\text{--}20 \text{ t/ha}^{-1} \text{ year}^{-1}$), very high ($A = 20\text{--}40 \text{ t/ha}^{-1} \text{ year}^{-1}$), and severe ($A = 440 \text{ t/ha}^{-1} \text{ year}^{-1}$). However, for the current study, four erosion classes were adopted. The soil loss map (Fig. 7) obtained in this study predicted that 4 erosion classes dominate the area. The four erosion classes are described in this study as follows: $0\text{--}2 \text{ t/ha}^{-1} \text{ year}^{-1}$ (very low erosion rate), $2.1\text{--}4.0 \text{ t/ha}^{-1} \text{ year}^{-1}$ (low erosion rate), $4.1\text{--}6.0 \text{ t/ha}^{-1} \text{ year}^{-1}$ (moderate or medium erosion rate), and $> 6.0 \text{ t/ha}^{-1} \text{ year}^{-1}$ (high erosion rate). Very low and low erosion classes mostly characterize the northern portion of the study area, whereas a

Fig. 7 Map showing the predicted annual soil loss rates across Anambra State



moderate soil erosion rate characterizes the western portion. However, the eastern and southern parts of the State are generally dominated by high erosion rates (Fig. 7). Overall, the soil loss results suggest that about 5% (242.2 km²) of the total study area have very low erosion risk, 25% (1211 km²) show low erosion risk, 30% (1453.2 km²) have medium risk, and 40% (1937.6 km²) show high risk.

The observations made from Fig. 7 seem to correlate very well with the interpretations of the individual RUSLE factors. This implies that geoenvironmental factors mainly control the erosion risk in the State. Hence, the soil loss values can vary notably due to changing climatic (Kayet et al. 2018) and other environmental conditions. It is pertinent to note that the areas within the eastern and southern portions of the study area are underlain by weak and poorly consolidated geologic formations — the Nanka, Ogwashi, and Benin (the coastal plain sand) formations (Fig. 2). Moreover, the soil types in these regions have been described to be more vulnerable to erosion. On the other hand, the western part of the State is mostly underlain by alluvial sediments. In contrast, the northern portion of the study area has both alluvial sediments and Imo Shale deposits. It was also noticed that the soil loss rates in the study area are spatially linked to and controlled by the slope distribution, topographic configuration, rainfall erosivity, and the LULC.

Thus, it is realized that the soil loss is more in the areas with higher-slope angles and lengths, elevations, drainage density, rainfall erosivity, thicker sedimentary deposits, and low (sparse) vegetation cover. Even if the vegetation cover was to be high in these areas, the nature of the topography and rainfall erosivity would jointly work to annul the protective impact of the vegetation. Previous authors have reported similar cases (Kumar and Kushwaha 2013; Yadav et al. 2005; Dutta et al. 2015) who observed that erosion risk was high in afforested regions with dense forests but have dissected hilly terrain with steep slopes and higher *LS*-factor values. Moreover, the parts with human settlements (with low *P*-factor) in the eastern and southern portions were also observed to have high erosion risk due to the topography. However, the agricultural lands in the northern and southwestern portions of the State (with lower *LS*-factor values) have lower erosion risks than the eastern and southern portions (Figs. 5 and 6). These observations indicate that the *LS*-factor plays a higher role in determining the pattern of potential erosion risk zones across the study area.

Generally, most of the State were observed to experience very low to moderate erosion risks. The current research findings seem to be within the tolerable erosion risk limits (Das et al. 2018; Morgan 1995; Koirala et al. 2019). However, the results (Fig. 7) have shown that the areas with the

maximum erosion risks are the critical areas that are much more susceptible to erosion, thus needing more mitigation and environmental management strategies.

Validation of the RUSLE model

Although most previous studies that utilized the RUSLE model and geoinformatics techniques for soil loss assessment did not integrate statistical metrics for the validation of their models, it was seen as a necessary step in the present study to use a statistical metric for model validation. In this paper, the area under curve (AUC) value of receiver operating characteristics (ROC) was used for assessing the accuracy rating of the RUSLE model (Fig. 8). This statistical metric has been widely used for the validation of weighted overlay landslide and flood susceptibility models (Ozioko and Igwe 2019; Darabi et al. 2021). Traditionally, ROC curves are plotted to show the relationship between true-positive and false-positive rates. While the true-positive rate may be represented as sensitivity, the false-positive rate may be represented as 1-specificity. The AUC obtained in the current study is 0.715, indicating that the produced RUSLE model is reliable. Generally, an AUC value close to 1 indicates an ideal model (Egbueri 2021; Ozioko and Igwe 2019). The result of the AUC obtained in this study suggests that the model provides reliable information that could be useful for soil erosion monitoring, assessment, mitigation, and management in the future.

Implications of the present study

The present study has indicated that steep and lengthy slopes, high rainfall erosivity, low vegetation cover, unregulated land use, and poor management practices, and loose soil type are the factors influencing high volumes of soil

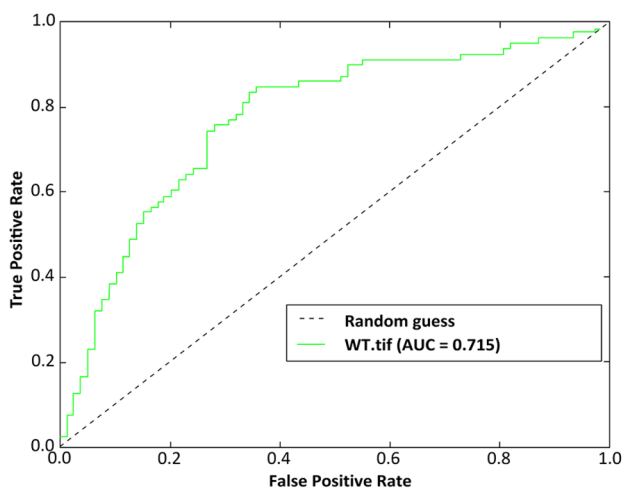


Fig. 8 Area under curve (AUC) value for validating the RUSLE model

loss in various parts of Anambra State. However, it appears that steep and lengthy slopes (*LS*-factor), loose soil type (*K*-factor), and high rainfall erosivity (*R*-factor) are the most important factors, given the observed peculiarities of the study region. Thus, areas with higher slopes, rainfall intensity, and ferralitic soils are more susceptible to soil loss. It has been estimated that the mean annual soil loss in the eastern and southern portions is $> 6.0 \text{ t/ha}^{-1} \text{ year}^{-1}$. Therefore, the priority areas with potential high soil erosion risk should be given urgent, proper, and effective soil conservation and management practices.

Having achieved the research objectives, it is believed that the findings of this project would be helpful in:

- Erosion susceptibility or risk prioritization and pixel identification of critical areas needing urgent reclamation and maintenance in Anambra State.
- Adequate urban and rural community planning, i.e., in identifying critical areas not so suitable for human settlement in the study area.
- Erosion hazard/risk monitoring, assessment, management, and soil conservation programs in the State and other regions.
- The selection of suitable engineering specifications and designs for the prevention and mitigation of soil erosion hazards in the State.
- Advancing soil erosion research, locally and internationally.

Conclusions

This study integrated the RUSLE model and geoinformatics in assessing the erosion risk of Anambra State in southeastern Nigeria. The study approach has successfully predicted the relative spatial patterns of places with varying risks of soil erosion in the State. The average annual soil loss was estimated to range from very low to high risks. The research findings revealed that the study area's majority (about 70%, 3390.8 km² out of 4844 km²) are at moderate to high soil erosion risks. Overall, the northern portion of the study area is characterized mainly by very low and low erosion classes, whereas the western portion is characterized by moderate soil erosion rate. Nevertheless, the eastern and southern portions of the State are dominated by high erosion rate. The *R*, *K*, and *LS* factors seem to largely influence the soil loss in the area more than the *C* and *P* factors. A close correlation was observed between the extent (risk) of soil erosion and the area's slopes, rainfall patterns, and soil types. This study provided satisfactory results for estimating soil loss in Anambra State, and the results would serve as reference with practical significances in erosion research, soil conservation, and management in the State. Thus, the information provided in this paper would be essential in assisting appropriate authorities in erosion management.

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Declarations

Conflict of interest The authors declare no competing interests.

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