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Multi Temporal Mapping and Severity Classification of Soil Erosion in Imo State Nigeria Using RUSLE and Cloud Based Geospatial Modelling

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Abstract

Soil erosion is one of the significant environmental issues in southeastern Nigeria. This is attributed to excessive rainfall, accelerated land-use and growing anthropogenic pressure. In this paper, the authors examined the spatiotemporal coverage of soil erosion in the Imo State through the Revised Universal Soil Loss Equation (RUSLE) embedded into the Google Earth Engine (GEE) cloud computing platform. The years 2017, 2019, 2021, 2023, and 2024 were processed in multi-temporal datasets of CHIRPS rainfall, SRTM digital elevation model, SoilGrids soil properties, as well as ESRI global land use/land cover data. Rainfall erosivity (R), soil erodibility (K), topographic (LS), and cover management (C) variables were produced and support practice variable (P) had a constant value of unity. Conclusions have shown that there is a high level of rainfall erosivity throughout the state where the average values of R-factor are over 1100 MJ mm ha⁻¹ h⁻¹ yr⁻¹. The erodibility value of soils was typically low (mean K = 0.032 t ha h MJ⁻¹ mm⁻¹) indicating medium resistance of the soil. The LS-factor was very spatially variable with the highest levels to 11.00 in the higher relief areas. The analysis of land use revealed that built-up grounds were increasing gradually; the areas under cropland and shrubland were decreasing, and the values of C-Factor were rising with time. Spatial heterogeneity of estimated soil loss was

significant, and the average annual soil loss was between 1.34×10^6 and $9.23 \times 10^6 \text{ t ha}^{-1} \text{ yr}^{-1}$. Oguta and Ohaji/Egbema LGAs had the severity of erosion and concentration of hot spots. The results show that land cover processes and topography are the most important factor in causing the variability of erosion in Imo State. The paper emphasizes the usefulness of the GEE-based RUSLE modelling in the large-scale evaluation of erosion and provides the scientific foundation of the specific planning of soil conservation efforts.

Keywords: Google Earth Engine; Spatiotemporal analysis; Land use/land cover; Erosion hotspots

1.0 Introduction

One of the most widespread geo-environmental issues impacting agricultural productivity and natural ecosystems all over the world is soil erosion (Al Shoumik et al., 2023; Borrelli et al., 2017; Ezeh et al., 2024). This is done by the breaking off and erosive movement of soil particles out of their place of origin and may eventually end up being deposited in streams and rivers and flood plains. This progressive depletion of topsoil with a high level of nutrients disrupts the biological and chemical properties of the soil to maintain the crop yield and biodiversity, in turn destabilizing the ecological balance and sustainability of the land in the long run (Ascencio-Sanchez et al., 2025; Okoli et al. 2026). Along with the decline in agriculture, the consequent sedimentation process is still damaging water resources and freshwater habitats (Palliyaguru et al., 2023). Erosion is almost equal to the soil formation under natural conditions, but with the pressure of humans it has significantly changed the situation. Land clearing and conversion of forests into farmlands have been enhanced by the growth in population and the growing demand in food. Past forecasts indicate that over 50 % of the total new farmlands created between 1980 and 2000 were the result of deforestation (Gibbs et al., 2010). In the opinion of the FAO Global Soil Partnership, the loss of soil on cultivated landscapes in the world reaches up to 75 billion tons of soil every year (FAO GSP, 2017). Borrelli et al. (2017) stated that Africa is one of the regions in the world that has one of the highest rates of agricultural land loss due to erosion. The recent literature shows that there is a tendency toward the increase of land degradation in most of the tropical areas, and the size of the land areas vulnerable to erosion is increasing (Erkossa et al., 2015). It is aggravated in areas where the removal of soils is higher than the natural replenishment of the sediment, frequently in areas affected by land-use activities that include mining, road building, mechanised agriculture, or extractive agriculture (Kanito et al., 2023; Pregnotato and D'Amico, 2011). It has been demonstrated that tiled croplands undergo an excessively high intensity of erosion as compared to

vegetated or undisturbed surfaces (Keesstra et al., 2016). This is further supported by Maetens et al. (2012) stated that runoff and sediment loss is significant on cultivated soils as opposed to vegetation stands. Several environmental and anthropogenic factors control the intensity of erosion, which include rainfall erosivity, slope gradient, vegetation cover, agricultural growth caused by population, land-use and land-cover changes, and climatic variability (Marondedze and Schutt, 2020; Srejeic et al., 2023; Usman et al., 2023; Wen et al., 2023; Aziz et al., 2024). The recent decades have demonstrated a close relationship between the anthropogenic climate variability and the accelerated rates of soil erosion, which makes more scientists agree that the factors of climatic variability and LULC dynamics are the leading causes of soil loss (Ochoa et al., 2016; Poesen, 2018; Panagos et al., 2021; Akaolisa et al., 2023). Knowledge of these drivers is important in terms of developing effective soil conservation plans and the sustainability of land stewardship. Further understanding of the erosion behaviour is hence necessary in setting the right land management and conservation behaviours (Palliyaguru et al., 2023; Nawazuzzoha et al., 2024; Naqvi et al., 2013). Steep slopes and poorly vegetated ground have a high erosion potential, particularly in the regions when human actions change hydrology of the surface and increase the rate of runoff formation (Fagbohun et al., 2016; Arega et al., 2024). The rapid growth of croplands, settlement areas, and vegetation clearing carried out due to the number of people is still exacerbating the risk of erosion in prone areas (Ascencio-Sanchez et al., 2025; Kanito et al., 2023). Another factor that has been identified as a significant cause of intensive soil erosion during high-energy rainfall is rainfall erosivity (Sanogo et al., 2023; Ayele et al., 2022). As a result, GIS-based erosion modelling has become one of the credible methods to measure the erosion processes, locate spatial hotspots, and rank the areas of intervention (Naqvi et al., 2019). The given models enable the assessment of erosion over extensive areas and provide the empirical foundation to the development of the conservation system (Arega et al., 2024; Lense et al., 2023; Usman et al., 2023). Imo state is also experiencing high soil erosion due to the same forces including population-related land conversion, agricultural intensification, and the rapid urban encroachment on the state, more so in the upland localities around the upland communities of Owerri, Ideto, Okigwe and Orlu and its rural catchments. Spatio-temporal evidence that can measure the erosion trend over the 27 LGAs that constitute Imo State is scarce even though this can be subject of study because of its vulnerability. Knowledge about erosion processes in the state plays a significant role in state government planning, protection of watersheds, and specific conservation policy. This study

therefore uses the RUSLE model within GIS based environment to assess the trends of soil erosion in Imo State between 2017 and 2025 (2024 as the proxy) after every two years. The objectives are to: (1) define the key drivers that have affected the distribution of erosion in Imo State; (2) determine the level and temporal change in the soil loss during the study period; and (3) to categorise and rank LGAs based on their severity of erosion to facilitate their prioritised work in land restoration and management. The work offers fresh spatial data to the erosion patterns in the state of Imo and provides a body of knowledge to be used in the development of sustainable conservation programs based on the LGAs.

2.0 Study Area and Data

This research paper is centered on the state of Imo, which is in the southeast of Nigeria. On the administrative level, the State has 27 Local Government Areas (LGAs) (Fig. 1). It is typified by both fast-growing city areas and highly populated countryside (Okoli et al. 2026). The State capital, Owerri, is a big administrative and business hub with other important towns being Orlu, Okigwe, Mbaise, Mbano, Oguta, Omuma, Ideto, Nkwere, and Okwelle. Imo borders Anambra State on the north, Rivers and Akwa Ibom States on the south, Enugu and Ebonyi States on the northeast and Abia State on the east and southeast (Fig. 1). As the population density steadily increases, and the pressure on land cover grows, the State experiences a growing surface degradation and erosion vulnerability in southeastern Nigeria, which is closely related to population density (Ayadiuno et al., 2022; Ezech et al., 2024; Okoli et al., 2024).

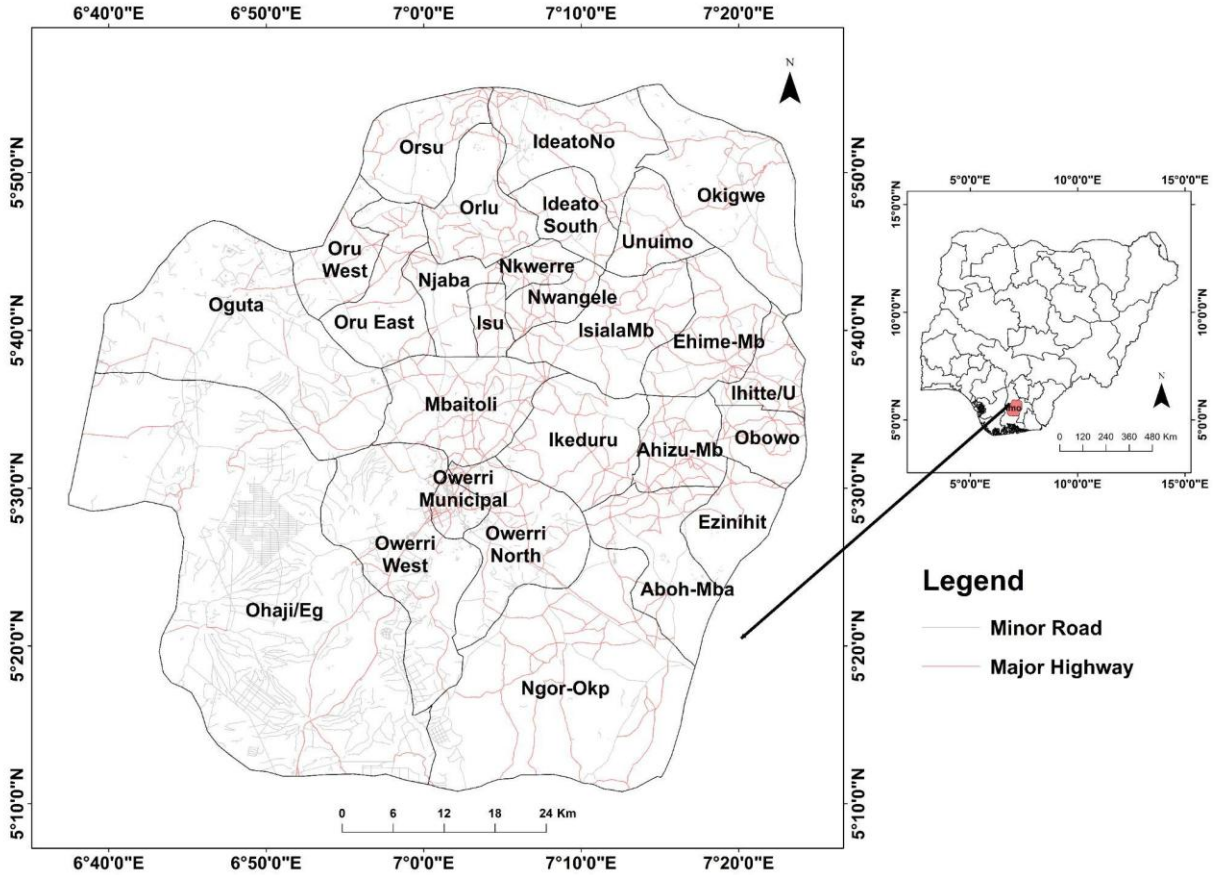


Figure 1: Map of Imo State, Nigeria showing the 27 LGA's

2.1 Data Sources

The datasets (Table 1) used in the study have been chosen according to the criteria of easy retrieval, preprocessing and computation in Google Earth Engine (GEE) platform. The data on precipitation provided by rainfall was downloaded via the Climate Hazards Group InfraRed Precipitation offered in Google Earth Engine (UCSB-CHG/CHIRPS/DAILY) with a resolution of about 5 km. The soil features needed to estimate soil erodibility were based on OpenLandMap datasets of soil fractions globally (sand, silt, clay and organic matter). Topographic parameters were calculated in the Shuttle Radar Topography Mission (SRTM) digital elevation model and flow accumulation was calculated in the MERIT Hydro data (Slimani & Boukhemacha, 2025). The land use and land cover data were obtained using ESRI Global Land cover Time Series dataset with a spatial resolution of 10 m (Umoh et al., 2024). The support practice factor (P) was taken to be unity because the data on spatially explicit conservation practice was not available, as identified in the past research. The time frame of the study is 2017-2025 with the analysis period of every two

years. Rainfall, soils, topography and land cover are part of the data and this is all incorporated in the RUSLE modelling framework.

Table 1: Geospatial Datasets, Sources, Spatial Resolution, and RUSLE Factor Applications

Dataset	Source (GEE Compatible)	Spatial Resolution	Application in RUSLE
Rainfall	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015) – GEE: UCSB-CHG/CHIRPS/DAILY	~5 km	Rainfall erosivity (R-factor)
Soil Properties	OpenLandMap soil fraction datasets (sand, silt, clay, organic matter) – GEE: OpenLandMap/SOL/...	250 m	Soil erodibility (K-factor)
DEM	Shuttle Radar Topography Mission (SRTM) – GEE: USGS/SRTMGL1.003	30 m	Slope derivation
Flow Accumulation	MERIT Hydro global flow direction & accumulation – GEE: MERIT/Hydro/v1.0.1	90 m	Upslope contributing area
Land Use / Land Cover	ESRI Global Land Cover Time Series (Karra et al., 2021) – GEE: projects/sat-io/open-datasets/landcover/ESRI Global-LULC 10m TS	10 m	Cover management (C-factor)
Support Practice	Assumed constant ($P = 1$) due to absence of spatial conservation data	–	Support practice (P-factor)

All datasets were accessed, clipped to the Imo State boundary, and processed using the Google Earth Engine Code Editor workspace. ArcGIS Pro was subsequently employed for spatial visualisation, severity ranking, map production, and LGA-based statistical summaries.

3.0 Methodology

3.1 Data Preprocessing

All the datasets needed to compute the RUSLE have been accessed and processed on the Google Earth Engine (GEE) cloud platform to facilitate effective processing of multi-temporal datasets

over the period of the study (2017-2025). The variables of rain, soil texture, DEM and land-cover layers were clipped on the Imo State boundary and transformed to spatially normalized rasters to be used in further factor derivation. The spatial results were also exported to ArcGIS Pro to create maps, classify them, help with visual analytical tools, and extract zonal statistics and LGA level. R- factor surface was computed with the annual CHIRPS rainfall sequence by the use of raster expressions in GEE. Classes of land-cover were redesignated into C-factor classes using values borrowed in the recent literature, and transformed into raster form to be modelled. The LS-factor was calculated based on the 30 m SRTM DEM with a modified Wischmeier and Smith (1978) terrain expression, as a slope and flow accumulation functions. The K-factor soil attributes were derived on SoilGrids/iSDA layers and calculated using the GEE (Ezeh et al., 2024). The figure of methodological flow is provided in Fig. 2.

3.2 RUSLE Model

The Revised Universal Soil Loss Equation (RUSLE) integrates five independent environmental factors whose multiplicative interaction estimates the rate of soil loss across a landscape (Eq. 1). Its adoption is well established in erosion risk studies owing to its robustness and high transferability (Alewell et al., 2019; Benavidez et al., 2018; Ghosal & Bhattacharya, 2020).

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

Where A is the average annual soil loss ($\text{t ha}^{-1} \text{ yr}^{-1}$); R represents rainfall erosivity ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$); K is the soil erodibility factor ($\text{t h MJ}^{-1} \text{ mm}^{-1} \text{ ha}^{-1}$); LS denotes the combined slope length and slope steepness factor; C represents the land-use/vegetative cover factor; and P accounts for conservation support practices. Except for R and K , all factors are dimensionless.

3.2.1 Rainfall Erosivity (R-factor)

R-factor measures the kinetic energy of precipitation and its capacity to loosen the soil particles (Renard et al., 1997). Since only a few records of sub-hourly rainfalls in southeastern Nigeria were available, erosivity was determined based on the equation by Roose (1977) (Eq. 2), which has been commonly employed in the erosion research in West Africa (Andreoli, 2018; Rozos et al., 2013; Ezeh et al., 2024). The datasets of CHIRPS were used to compute the total rainfall as an annual amount and transformed into grids of erosivity in each of the intervals. Spatial continuity has been delivered through IDW interpolation which is known to provide reliability on the rainfall surface modelling (Tsegaye & Bharti, 2021).

$$R = 0.5 \times AR \quad (2)$$

Where AR = mean annual rainfall, R = erosivity index. Erosivity values typically range between 1500–3000 MJ mm ha⁻¹ h⁻¹ yr⁻¹ in humid West African settings (Andreoli, 2018).

3.2.2 Soil Erodibility (K-factor)

The erodibility is a measure of the susceptibility of soil to erosion and liquidity (Naqvi et al., 2013). Its main control is exercised by the arrangement of particles (sand-silt-clay ratio), organic matter and permeability (Renard et al., 1997). The lack of local laboratory measurements in the study led to the use of Williams (1995) equation to estimate K-factor that has been commonly used in models of erosion in the tropics (Tsige et al., 2022). DF of soil texture of SoilGrids/iSDA rasters were fed into the K-computational equation in GEE. The field behaviour was reflected in the fact that high silt content was associated with increased erodibility whereas the areas with high clay and sand content showed reduced detachment susceptibility (Nill et al., 1996; Ostovari et al., 2022).

3.2.3 Topographic (LS-factor)

LS-factor is used to explain the topographic effect on erosion and is a combination of the slope gradient and slope length (Wischmeier and Smith, 1978). The DEM-derived slope (%) and flow accumulation layers were combined to produce LS surfaces based on the formulation of percentage-slope which is appropriate to a landscape with moderate through steep gradient transition like portions of Okigwe, Orlu and Mbano (Nakil & Khire, 2016). Slopes with a steeper gradient and longer length increased sediment transportation and concentration of runoff as per the observations made in Merchan et al. (2023), Pitt (2004) and Ziadat and Taimeh (2013).

$$LS = \left(\frac{\text{flow accumulation} \times \text{resolution}}{22.13} \right)^m \times \left(\frac{\sin(\text{slope})}{0.0896} \right)^n \quad (3)$$

Where s is slope %, and flow accumulation represents potential runoff pathways.

3.2.4 Cover Management (C-factor)

C-Factor considers the effects of vegetation shielding and the exposure of bare soil when land use changes (Chang et al., 2016). The ESRI 10 m land-cover data were reclassified to seven classes and an established value of C assigned according to previous literature. The values of rangeland, forested land, cropland, and bare surface were 0.15, 0.08, and 0.38, respectively (Zanchin et al., 2021; Benavidez et al., 2018; Koirala et al., 2019). Constructed spaces especially in the areas surrounding Owerri, Orlu and highly compacted villages and towns have a high level of impervious cover in between bare fields, therefore characterized with 0.8 like Ezech et al. (2024) and Egbueri et al. (2022).

3.2.5 Conservation (P-factor)

P-factor is a measure of erosion-reduction benefits of conservation activities including terracing or contour farming. Nevertheless, due to the size of analysis and the lack of spatially explicit conservation data, P was set to 1, which is seen as the case when P-data are missing (Ajibade et al., 2020; Borrelli, 2011; Ghosal and Bhattacharya, 2020).

3.2.6 Erosion Severity Classification

In order to enhance interpretation and prioritisation, the estimated annual soil loss maps were categorised into the levels of soil erosion severity using standard thresholds that were used in RUSLE-based research. The values of soil loss that were continuous were redefined into five levels namely; very low, low, moderate, high and severe erosion. This classification provided the possibility of the spatial comparison of the intensity of erosion across LGAs and determining areas that needed immediate intervention. Zonal analysis was then applied to the severity maps in order to calculate mean severity values per LGA.

3.2.7 Hotspot Analysis

Erosion hot spot analysis was carried out to determine areas that had remained high in soil loss in the state. The mean soil loss map was subjected to a 90th percentile threshold-based method, in which those areas where the values of erosion were in the upper percentile were identified as hotspots. These hotspots were removed and analysed spatially with zonal statistics in order to measure the extent of the hotspots in each LGA. This method helped to identify LGAs with the significant concentration of erosion and the prioritisation of the erosion risk.

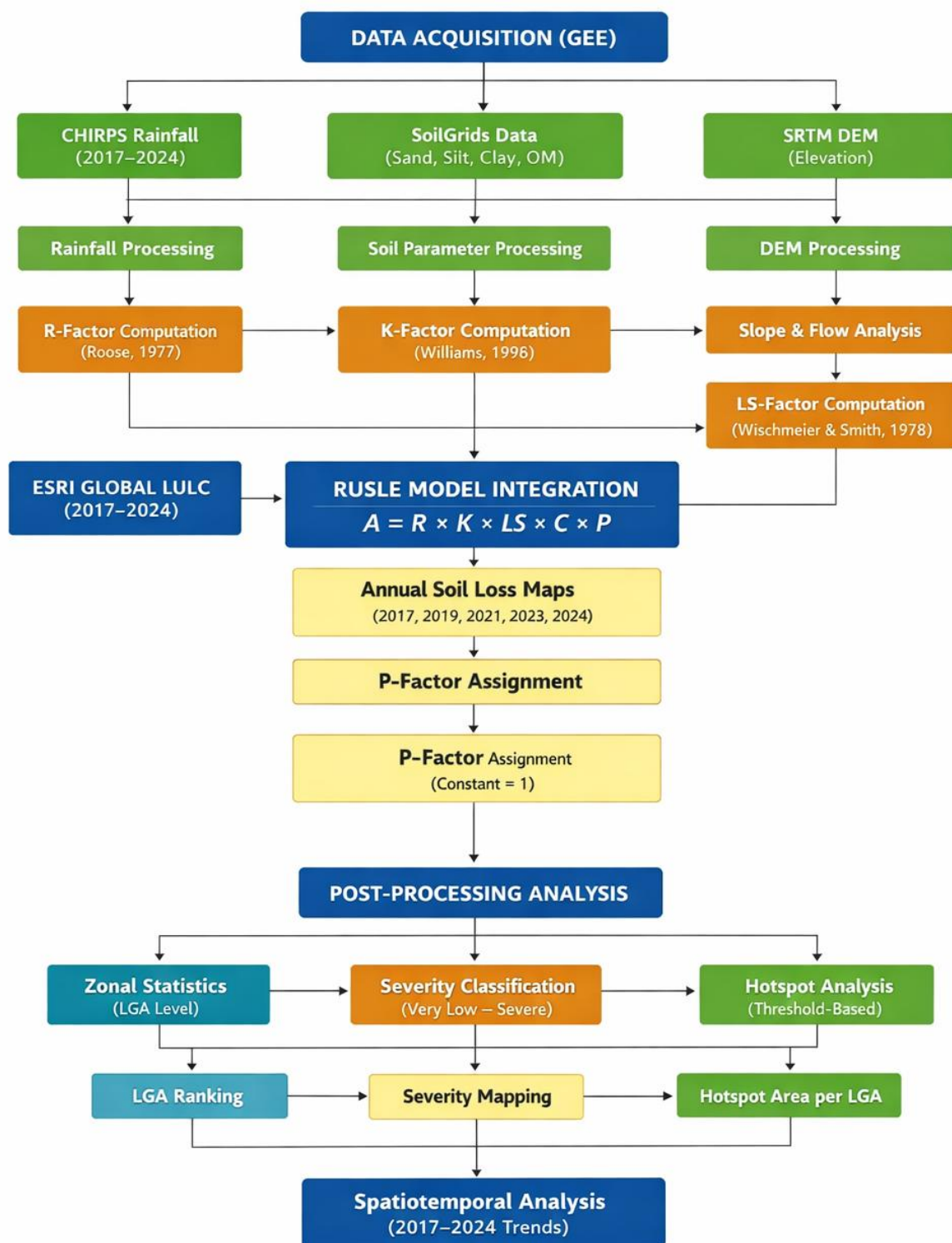


Figure 2: Methodological Flowchart Using GEE for Soil Erosion Modelling in Imo State

4.0 Results and Discussion

4.1 Rainfall and Rainfall Erosivity (R-Factor)

There was significant inter-annual variability of annual rainfall at Imo State between 2017 and 2025 (Figure 3a and 3b; Table 2). The small scale ranged between 1988.79 mm and 2750.55 mm in 2023 and 2019 respectively meaning that there are quite a few changes in the amount of moisture input over the years of study. The highest rainfall was experienced in the year 2019 with the highest value of 3259.42 mm and the lowest value of 1752.74 mm was recorded in 2023. The presence of these variations shows the alternating wet and comparatively drier years which are of dynamic nature of the tropical climate regime of the region. Rainfall distribution patterns in Imo state exhibit relatively homogenous distribution patterns with minor local deviations (Chukwudi, 2025). The LGAs in the south tended to have a little more rainfall than their counterparts in the north (which is in line with the coastal climatic effect of the Niger delta area). Southern-north rainfall gradients have been known in south-eastern Nigeria especially in Anambra State (Ezeh et al., 2025), supporting the local climatic coherence in the Lower Niger Basin. These rainfall patterns are further converted into erosive potential by the derived rainfall erosivity maps (Figure 3c).

Table 2: Annual Rainfall Statistics (2017 – 2025)

Year	Rainfall _{min} (mm)	Rainfall _{mean} (mm)	Rainfall _{max} (mm)
2017	2002.52	2276.60	2611.46
2019	2349.24	2750.55	3259.42
2021	2137.40	2581.28	3067.24
2023	1941.38	2264.04	2635.54
2025	1752.74	1988.79	2337.01

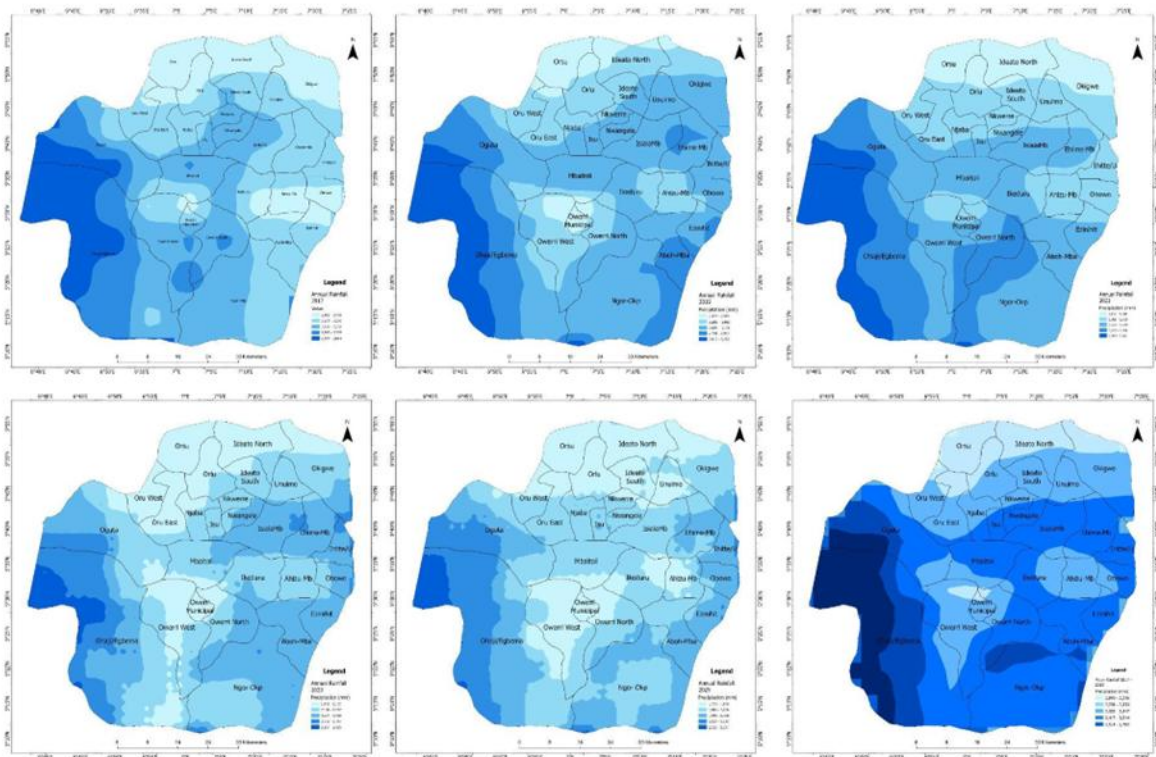


Figure 3a: Spatial variation of Annual rainfall 2017 - 2025 and Mean Annual Rainfall (2017-2025)

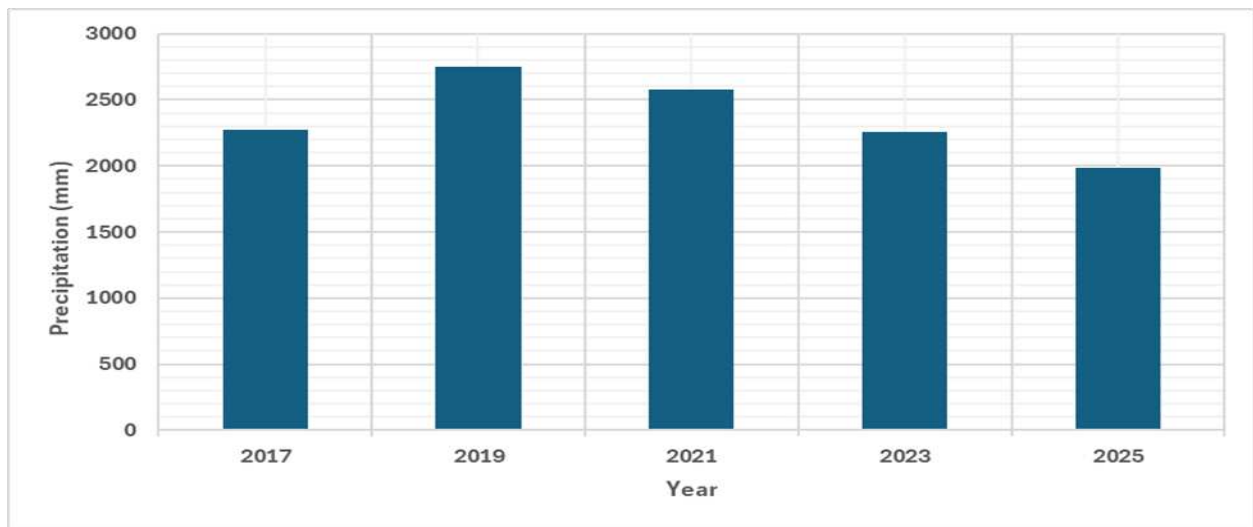


Figure 3b: Plots of annual rainfall from 2017 – 2025

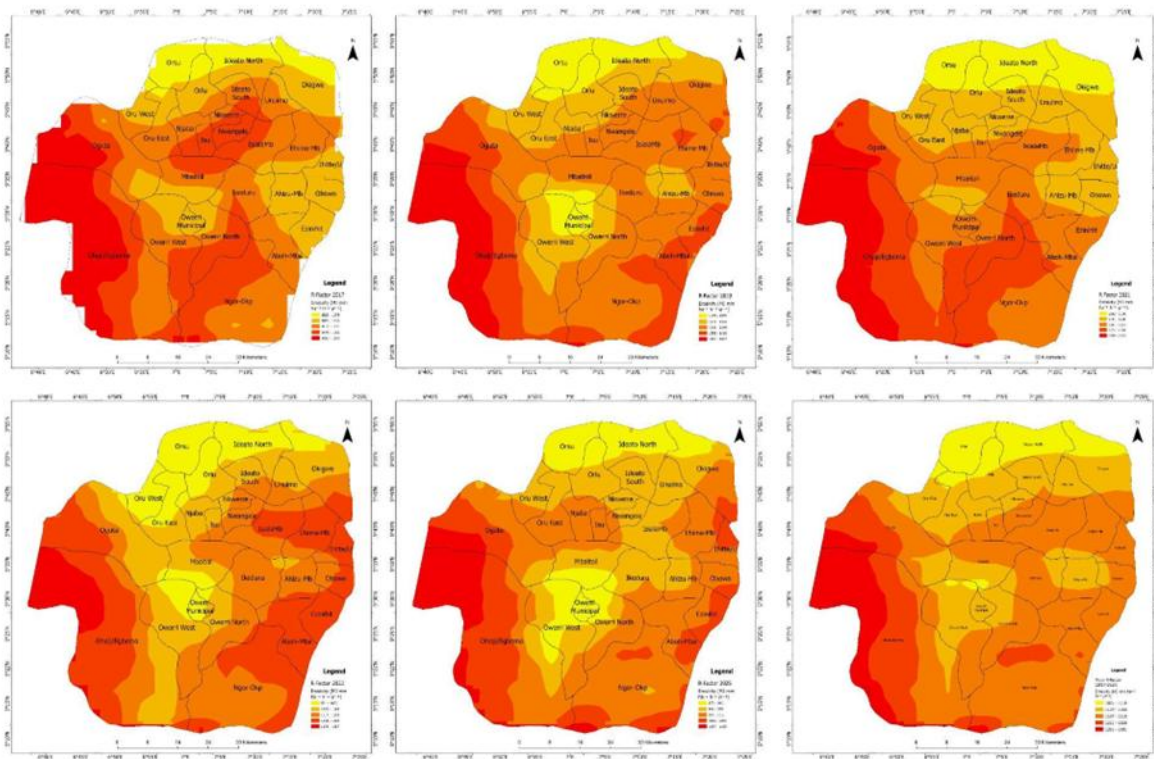


Figure 3c: Rainfall Erosivity maps 2017 – 2025

The values of R-factor were $1001.26 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ in 2017 up to $1629.71 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ in 2019 (noted in Table 3a). A notable period was 2019 which was the same year as the peak rainfall hence affirming that erosivity is highly dependent on the magnitude and intensity of rainfall. The values of the R-factor in 2017 and 2025 showed relatively lower values. This is an indication of low erosive rainfall energy in the same years. Table 3b showed that the multi-year mean R-factor during the period (2017-2025) was $1184.20 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ with highest and lowest value of $1391.07 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ and $1021.48 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ respectively. This denotes that the climate in Imo State is mostly high in erosiveness. Other similar magnitudes of erosivity were also recorded by Ezech et al. (2025) in the state of Anambra, with the values of the R-factor varying between 980 and $1680 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$. Time-based dynamics demonstrate that the R-factor values rose significantly in the years with wet weather (2019 and 2021) and fall in comparatively drier years (2023 – 2025). Nonetheless, the variations were not constantly monotonic which posits that inter-annual changes are mainly determined by a set of short-term climatic oscillations as opposed to long-term changes in rainfall. The present observation supports the results reported by Tegegne et al. (2022) in the Megech watershed, unkindly where the

variability in erosivity was also based on the year-to-year rainfall variations instead of long-term trends.

Table 3a: Annual Rainfall Erosivity (R-Factor) Statistics

Year	R _{fmin}	R _{fmean}	R_factor_max
2017	1001.26	1138.30	1305.73
2019	1174.62	1375.28	1629.71
2021	1068.70	1290.64	1533.62
2023	970.69	1132.02	1317.77
2024*	1004.4	1208.2	1431.7

Table 3b: Summary Statistics of RUSLE Input Parameters for Imo State

Model	Factor	Data Source	Method	Min	Mean	Max
RUSLE	R (Erosivity)	CHIRPS	Roose (1977)	1021.48	1184.20	1391.07
RUSLE	K (Erodibility)	ISRIC SoilGrids	Williams (1995)	0.010	0.032	0.058
RUSLE	LS (Topography)	SRTM DEM, MERIT Hydro	Wischmeier & Smith (1978)	0.00	0.0376	11.00

Summary statistics of rainfall erosivity (R), soil erodibility (K), and topographic (LS) factors computed for Imo State within the RUSLE framework.

4.2 Soil Erodibility (K-Factor)

The Imo State soils tend to be low- to medium-erodible as they comprise of sandy and clay soils with relatively low amounts of silt (Figure 4). The spatial distribution of the K-factor shows that the values are not without significant variation in the state as the values fall within the range of 0.021 to 0.058 t ha h MJ⁻¹ mm⁻¹ (Table 3b). The small range indicates that there is a low spatial variation in soil erosion sensitivity and this is also backed by the fact that the coefficient of variation of the statistical examination is small. On the spatial scale, the erodibility of the soil increases gradually eastwards to the western side of Imo State. The values of K-factor are concentrated mostly on the western LGAs with comparatively low values of the same making up

the northern and north-western regions. This spatial distribution is in line with the texture of soils in the state.

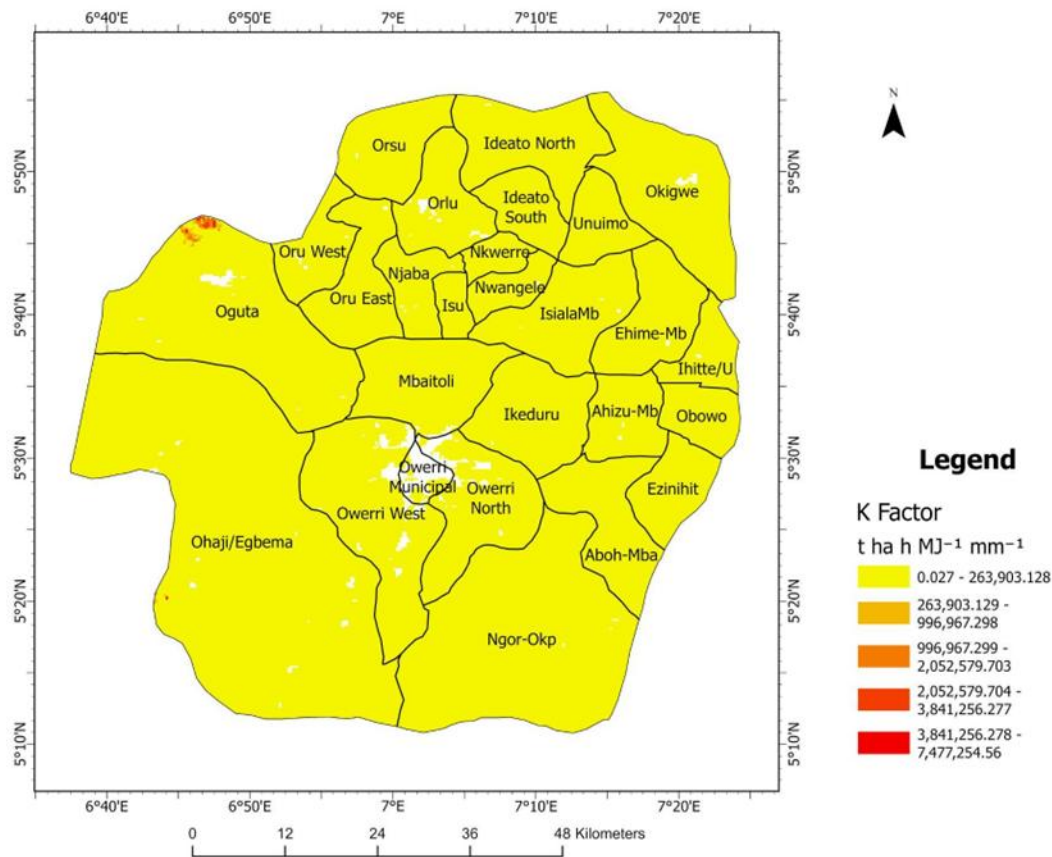


Figure 4: Soil Erodibility (k-Factor) Map

The soils in the south are mostly lateritic and moderately friable and these two factors support the aggregate stability but can be susceptible during heavy crushings of rainfall. Ebuei et al. (2022) conducted similar observations, reporting that at the same time, soils that are lateritic in the south east part of Nigeria have a moderate erodibility because of their structural properties and the content of organic matter. On the contrary, the soils of the northern and western regions of Imo State are mostly alluvial and their permeability is comparatively greater thus increased infiltration and reduced surface runoff. This property adds to their relatively lower values of erodibility that is in line with previous results in southeastern Nigeria (Fagbohun et al., 2016; Okpoko, 2018). The abundance of permeable zones reduces soil detachment due to less overland flow hence less risk of erosion during normal rainfall. Nonetheless, the field observations and prior researches show that such soils are more prone to erosion during the saturation period, especially at the end of the rainy season when the storms of high intensity are more common (Ezeh, 2023). In these situations,

the infiltration capacity reduces drastically leading to more surface runoff and soil loss. The phenomenon has been used to explain the occurrence of localized erosion features on some of the LGAs even though they have low erodibility ratings.

4.3 Topographic Influence (LS-Factor)

The slope and elevation features throughout the Imo State are highly spatially varied, as they represent the different geomorphological environment of the area (Figure 5). The slope extends between 0° – 41° yet the terrain is mostly composed of soft landscapes. Most of the state is in the 0 – 10° slope category which is mostly low-relief terrain. This dominance of the gentle slope is in line with the geology of the region, which is predominantly of sedimentary origin (southeastern Nigeria) and in concurrence with the previous regional measurements (Fagbohun et al., 2016; Ezech et al., 2025). Steeper slopes are mainly located at the north and north-eastern region of the state specifically at the localized upland terrains of Okigwe and Isiala Mbano LGAs. The western and southern floodplain areas have lower slope gradients and particularly along the river valleys related to the Imo and Njaba river systems. The relief of these low areas is low, and they are more easily affected by the erosion of sheets during prolonged rainfall. Tegegne et al. (2022) also reported a similar slope-controlled erosion processes in the Megech watershed of Ethiopia where flat lands were subjected to widespread surface runoff despite low slope angles. Analysis of elevation also shows that the Imo State is mostly located in the moderate altitude with the elevations majorly exceeding the 50 m above sea level.

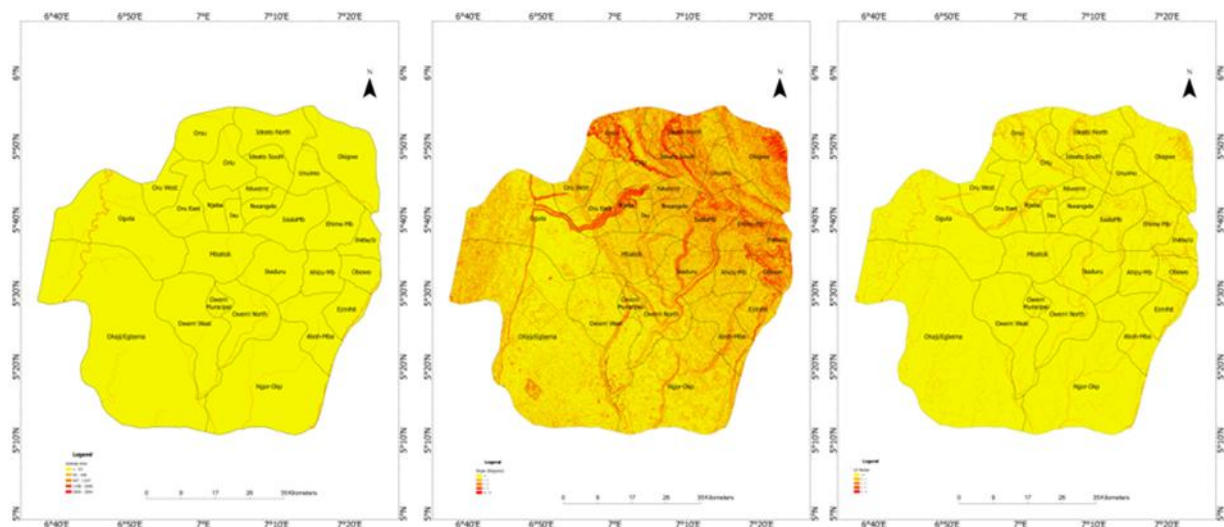


Figure 5: Topographic LS map

The high elevation areas are restricted to the isolated uplands located in the North of the state, and large lowlands on the southern coastal plains. This kind of elevation contrast has a direct impact on runoff velocity and accretion of flow, which directly affect the potential of erosion (Panagos et al., 2015; Borrelli et al., 2017). The obtained LS-factor map (Figure 5) shows the range of values between 0 and 11.00, and the average value of 0.038 (Table 3c). Since the average LS-factor is rather low, there are considerable high local values, especially in those regions, when the slope is steeper and the contribution area is more upslope. These high LS-factor areas are primarily focused in Okigwe, Ihitte Uboma and Isiala Mbana LGAs, which is a combination of slope steepness and flow accumulation. The large LS values show that there is great spatial heterogeneity of topographic control over erosion processes. The same trends have been documented in other tropical systems with local steep slopes non-proportionally contributing to the total sediment delivery (Moore and Nieber 1989; Desmet and Govers 1996). Wischmeier and Smith (1978) found that the risk of erosion is proportional to the squares of slope length and steepness, thus the high values of LS-factor in the upland areas. The mean LS-factor is relatively low, which indicates that topography is not the most important factor in erosion in the majority of Imo State. Nevertheless, where there is a coincidence of moderate slopes and high upslope contributing areas, then the risk of erosion is greatly increased. This observation is consistent with the results by Benavidez et al. (2018), who highlighted the fact that slope length tends to dominate erosion in humid tropical settings than the slope angle. Ezeh et al. (2025) recorded a mean LS-factor of 1.22 in Anambra State which is steeper and more dissected terrain. Relatively milder topography is therefore reflecting in the lower mean LS-factor observed in Imo State, though high-risk areas are still found in local areas.

Table 3c: LS Factor Statistic

Factor	Flow Source	LS factor _{max}	LS factor _{mean}	LS_factor _{min}
LS	MERIT_Hydro	11.00128707	0.03764983332	0

4.4 Land Use/Land Cover and C-Factor Dynamics

4.4.1 Land Use/Land Cover (LULC)

The 2017, 2019, 2021, 2023 and 2025 (proxy 2024) land use/land cover (LULC) maps indicate some dramatic changes in spatial and temporal dynamics of the Imo State (Figure 6). Cropland (Class 2) is found to be the most dominant land cover of the study area during the study period, and it is the land cover that is found to have the highest area extent of about 3,333 – 3,896 km²

over the years (Table 4). This preeminence is a characteristic of the agrarian state in which subsistence and commercial agriculture forms some of the chief means of livelihood. Forest cover (Class 1) is still comparatively small with an area of 16.39 km² (2017) to 22.50 km² (2025), which means that there is a lot of land clearance and deforestation. Class 4 Built-up areas are experiencing a gradual increase in size with a growth rate of 5.33 km² in 2017 to 3.03 km² in 2025, which is a symptom of urbanisation and population growth, especially in Owerri metropolis and nearby LGAs. Bare surfaces (Class 5) also expanded notably, reaching over 110 km² in 2025, which may be linked to construction activities, sand mining, and vegetation clearance.

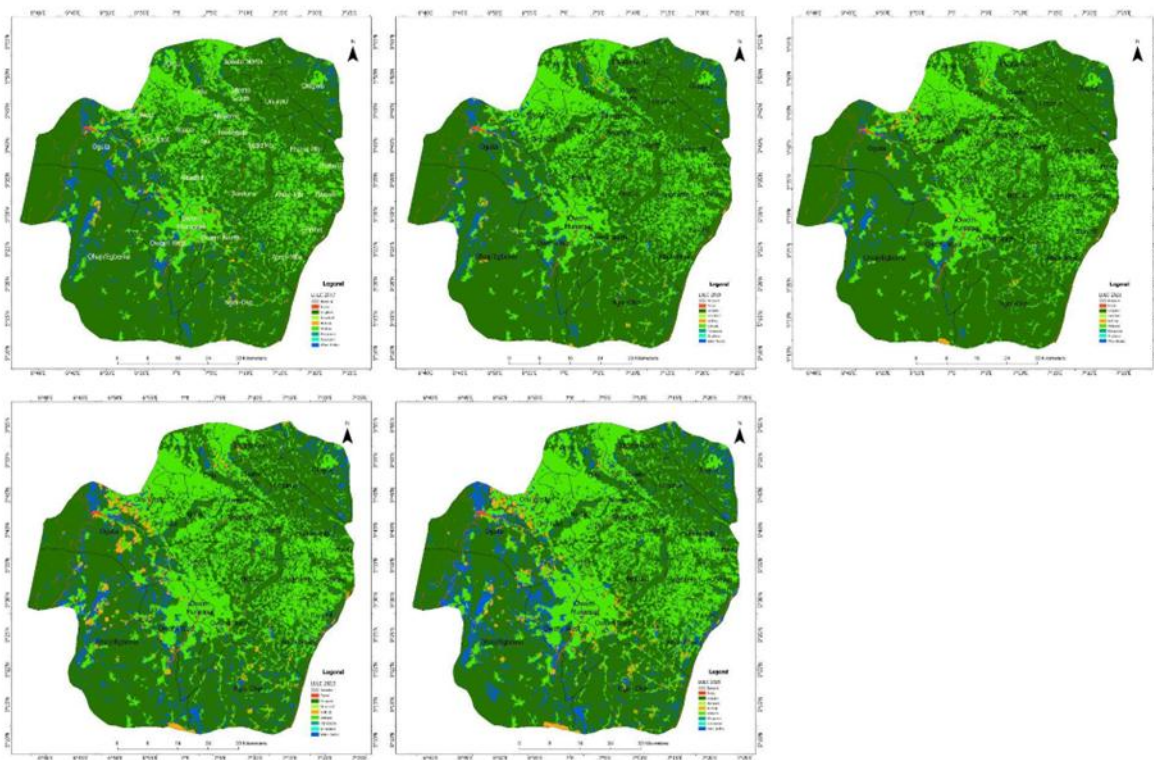


Figure 6: LULC maps 2017 - 2025 (proxy 2024)

Table 4: Land Use/Land Cover Area Statistics for Imo State (2017–2025)

LULC Class (Code)	2017 (km ²)	2019 (km ²)	2021 (km ²)	2023 (km ²)	2025 (km ²)
Forest (1)	16.39	20.82	22.35	21.60	22.50
Cropland (2)	3895.96	3831.21	3870.26	3332.76	3209.24
Grassland (4)	5.33	2.11	1.64	3.52	3.03
Built-up (5)	48.82	36.09	31.00	116.03	110.33

Wetland (7)	1081.79	1222.82	1257.01	1482.75	1498.67
Mangrove (8)	3.55	0.18	0.40	0.09	0.21
Shrubland (10)	9.28	2.50	0.83	0.10	0.85
Water body (11)	249.08	194.46	126.70	353.35	465.35

The low-lying floodplains and riverine environments are mostly dominant as wetlands (Class 7) cover large areas of the state, exceeding 1,000 km² in the majority of years. Classes of mangrove and shrubland (Classes 8 and 10) have the relatively small areal extents and show inter-annual changes, presumably due to seasonal flooding and anthropogenic disturbances. Water bodies (Class 11) grew significantly in 2023 and 2025, which is in line with a stronger rainfall and surface runoff environment, which was experienced in those years. The LULC dynamics point to the fact that vegetation is becoming less progressive with a conversion to land that has direct implications to soil erosion susceptibility. Ebueri et al. (2022) and Ezech et al. (2025) have reported similar trends of land cover degradation in southeastern Nigeria, crediting the processes to urban growth, agricultural development, and population increase.

4.4.2 Cover Management (C-Factor)

C-factor based on LULC was between 0 and 1 in all years of study because conditions of surface covers varied widely (Table 5). The average C-factor values were gradual ranging between 0.836 (2017) and 1.237 (2025) showing that there is a decrease in the protective vegetation cover with time. This is the same trend as the decrease in the number of forested and shrub covered landscapes and the increase in bare and developed surfaces. The values of C-factor are high in space when city centres are found and land is intensively cultivated especially in areas surrounding Owerri, Orlu and Okigwe axes (Figure 7). The lower ones fall in the wetland dominated and residual forested habitats of the western and northeastern regions of the state. The realized rise in the mean C-factor indicates the increasing susceptibility of soils to erosions since vegetation is very important in interception of rainfall, minimizing the effects of raindrops and reducing surface runoff (Renard et al., 1997). The time series trend shows that C-factor steadily increases meaning a loss of vegetation. The trend can be compared to the results of Ezech et al. (2025) in Anambra State and Ghosal and Bhattacharya (2020) in India because in both cases, urban growth and land-use change were identified as major contributors to the increase in erosion.

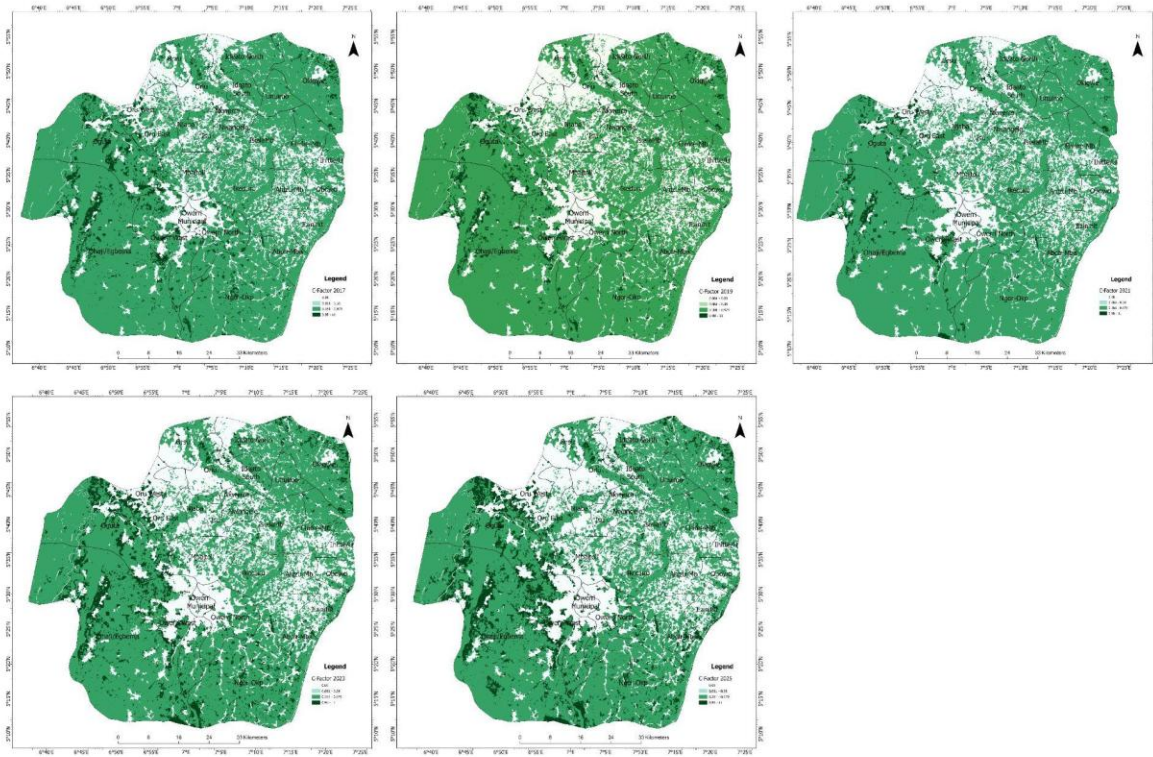


Figure 7: C-Factor maps 2017 - 2025

4.4.3 Support Practice (P-Factor)

The P-factor was taken as a constant of 1 throughout the study area, implying that there were no large-scale erosion control mechanisms which included terracing, contour farming or strip cropping. This supposition is in line with the common practice of erosion research in both natural and unregulated settings (Ajibade et al., 2020; Ghosal and Bhattacharya, 2020). The negligence of a unity P-factor means that the estimates of soil loss only indicate the effect of rainfall, soil properties, topography, and land cover with no mitigating impact of conservation measures. The net impact of the LULC change and the growing value of C-factor points to a growing susceptibility to erosion throughout Imo State. The conversion of the vegetated surfaces into agricultural lands and built-ups has increased the speed of the runoff generation and the erosion of sediments that has been avoided through the protection of the surface.

Table 5: C-Factor Statistics for Imo State (2017–2025)

Year	C _{max}	C _{mean}	C _{min}
2017	1.00	0.8357	0.08

2019	1.00	0.7051	0.08
2021	1.00	0.5650	0.08
2023	1.00	1.0152	0.08
2025	1.00	1.2366	0.08

4.5 Soil Loss Estimation (A-Factor)

The annual soil loss (A-factor) maps derived from the RUSLE model for 2017, 2019, 2021, 2023 and 2025 (Figure 8) show pronounced spatial variability across Imo State. The means of the soil lost are evaluated between 0 and $2.45 \times 10^{11} \text{ t ha}^{-1} \text{ yr}^{-1}$ with the maximum being $2.45 \times 10^{11} \text{ t ha}^{-1} \text{ yr}^{-1}$ in 2019, and the minimum being $1.75 \times 10^{11} \text{ t ha}^{-1} \text{ yr}^{-1}$ in 2025 (Table 6). The mean annual soil loss values are significantly different and are highest in 2019 in $2,612,590.63 \text{ t ha}^{-1} \text{ yr}^{-1}$ and lowest in 2021 in $923,453.10 \text{ t ha}^{-1} \text{ yr}^{-1}$, which suggests that the risk of soil erosion is high in general throughout the state. Severe soil erosion is also largely centred in the central and southern regions of Imo State which correlate with high levels of rainfall erosivity, high LS-factor values, and low vegetation cover. The inter-annual changes of soil loss have been observed to be the changes in the intensity of rainfall and land cover conditions. The high erosion values in 2019 are associated with the peak values of rainfall and higher values of R-factor in 2019. Lower amounts of soil loss in 2021 – 2025 can be saved by the fact that rainfall was relatively lower, and the state of surface cover was better. The findings affirm that the topography and land use dynamics and rainfall erosivity are the strong control factors of soil erosion in the Imo state which leads to the necessity of the timely soil conservation and sustainable land management interventions (Nwilo et al., 2021; Zumara and Nasher 2024; Nigussie et al., 2025).

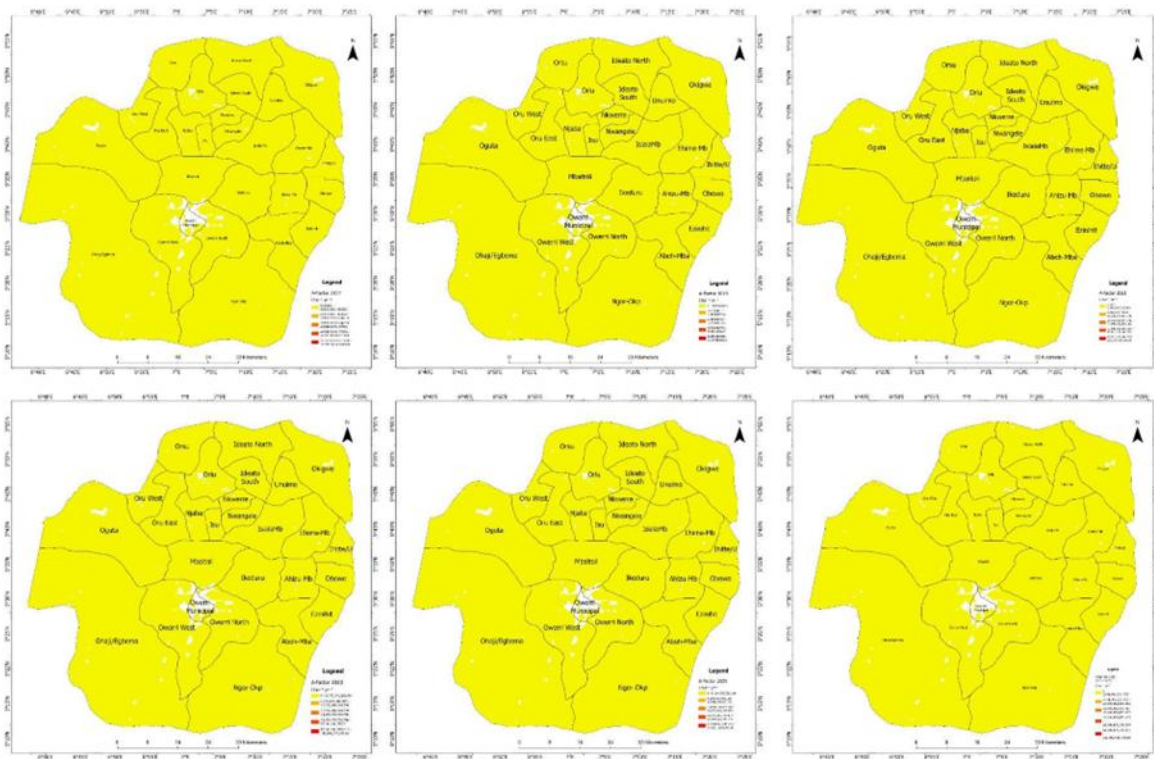


Figure 8: A Factor maps and mean soil loss 2027 -2025

Table 6: Annual Soil Loss (A-Factor) Statistics for Imo State (2017–2025)

Year	A_{max} (t ha ⁻¹ yr ⁻¹)	A_{mean} (t ha ⁻¹ yr ⁻¹)	A_{min}
2017	2.03×10^{11}	1,336,909.82	0
2019	2.45×10^{11}	2,612,590.63	0
2021	2.39×10^{11}	923,453.10	0
2023	1.99×10^{11}	1,817,146.26	0
2025	1.75×10^{11}	1,852,086.08	0

4.6 Severity Classification and Hotspot Analysis

These erosion severity tests are presented in figure 9. The mean severity of erosion values is between 1.02 and 2.47, which means that the erosion risk is mainly moderate in all the LGAs. The maximum degrees of severity were registered in the LGAs of Oguta (2.47), Orsu (2.18) and Ohaji/Egbema (1.81), whereas relatively lower severity rates were registered in Ahiazu-Mbaise (1.02), Nwangele (1.02) and Isu (1.03) LGAs (Table 7a). Such spatial patterns are in good agreement with the regions of intensive land-use change and surface runoff potential. At the LGA

level, erosion ranking (Table 7a) shows that Oguta LGA is the most susceptible area with exceptionally high means of annual soil loss at $1.88 \times 10^7 \text{ t ha}^{-1} \text{ yr}^{-1}$. Conversely, the lowest erosion magnitudes (less than $1 \text{ t ha}^{-1} \text{ yr}^{-1}$) were observed in Ahiazu-Mbaise, Nwangele, and Isu indicating to a stable land cover and a mild terrain. Change detection analysis (2017 – 2025 - proxy 2024) denotes the strongest increase in the soil loss in the LGAs of Oguta ($+5.78 \times 10^6$), Ohaji/Egbema ($+6.59 \times 10^3$), Orsu ($+4.84 \times 10^3$) and Orlu ($+1.75 \times 10^3$), which implies the rapid acceleration of land degradation with time (Table 7a).

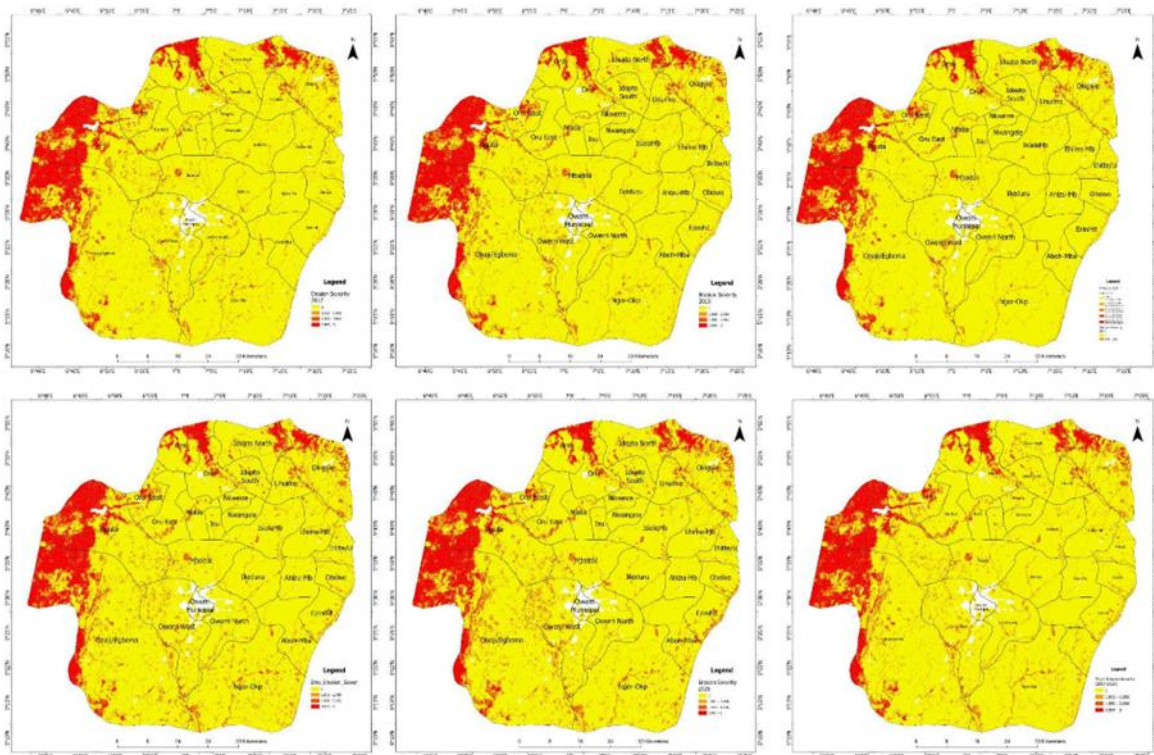


Figure 9: Erosion severity maps 2017 – 2025

the marginal losses were recorded in Oru West (-12.30) and Nkwere (-0.05) maybe due to a localized vegetation recovery or better land management. Hotspot mapping establishes high levels of spatial clustering of intense erosion areas. The highest level of hotspots was in the Oguta LGA (21.42 km^2), then Ohaji/Egbema (9.21 km^2), and Orsu (1.89 km^2). The other LGAs had hotspots areas of negligible or zero value suggesting very localized processes of erosion. These hotspots are in line with floodplain habitats, oil exploration areas and sites of high urban growth, where vegetation clearing and soil disturbance are common. The combined severity and hotspot analyses reveal the fact that the southern Imo State is the most dangerous area in terms of erosion and such

territory needs to be prioritized. The predominance of low-moderate-risk category in all the LGAs (Table 8) highlights the importance of taking proactive soil conservation measures before the situation escalates to severe classes of erosion. These results are consistent with previous regional research in which land-use pressure and hydrological change are related to the increased soil degradation in southeastern Nigeria.

Table 7a: Integrated Erosion Severity, Priority Index and Temporal Change per LGA

Rank	LGA	Mean Severity	Severity Class	Priority Index	Soil Loss Change (2017–2024)
1	Oguta	2.47	Severe	Very High	$+5.78 \times 10^6$
2	Ohaji/Egbema	1.81	Severe	Very High	$+6.59 \times 10^3$
3	Orsu	2.18	Very High	High	$+4.84 \times 10^3$
4	Orlu	1.74	High	High	$+1.75 \times 10^3$
5	Ideato North	1.56	Moderate	Moderate	+0.00
6	Okigwe	1.42	Low	Low	+0.00
7	Oru West	1.36	Low	Low	-12.30
8	Owerri Municipal	1.33	Low	Low	+0.00
9	Unuimo	1.31	Low	Low	+0.00
10	Njaba	1.29	Low	Low	+0.00
11	Ezinihitte Mbaise	1.27	Low	Low	+0.00
12	Ngor-Okpala	1.25	Low	Low	+0.00
13	Oru East	1.23	Low	Low	+0.00
14	Owerri West	1.22	Low	Low	+0.00

15	Ideato South	1.20	Low	Low	+0.00
16	Mbaitoli	1.18	Low	Low	+0.00
17	Obowo	1.16	Low	Low	+0.00
18	Owerri North	1.14	Low	Low	+0.00
19	Ehime-Mbano	1.12	Low	Low	+0.00
20	Ihitte/Uboma	1.10	Low	Low	+0.00
21	Isiala Mbano	1.08	Low	Low	+0.00
22	Aboh-Mbaise	1.05	Low	Low	+0.00
23	Ikeduru	1.04	Low	Low	+0.00
24	Nkwerre	1.03	Low	Low	-0.05
25	Isu	1.03	Very Low	Very Low	+0.00
26	Nwangele	1.02	Very Low	Very Low	+0.00
27	Ahiazu-Mbaise	1.02	Very Low	Very Low	+0.00

It was observed in Table 7b and Figure 10 that the highest extent of hotspots was recorded in Oguta LGA (21.42 km²), then in Ohaji/Egbema (9.21 km²) and therefore these areas were found to be the worst hit areas of erosion. In Orsu (1.89 km²) and Orlu (0.31 km²) moderate levels of hotspots were found and Idea North (0.0587 km²) and Okigwe (0.0015 km²) had little hotspots cover. The prevalence of hotspots in Oguta and Ohaji/Egbema points to the overlapping of hotspots to high intensities of rainfalls, the rising agricultural activities, the oil related land disturbances and the growing urban developments. The symptoms of these LGAs are a change in land cover and disrupted soils, which considerably increase the process of runoff and sediment transportation. The small size of the hotspots in Okigwe and Ideato North implies the relatively stable state of the

terrain and, consequently, a more favorable vegetation cover, which makes it less vulnerable to the massive erosion.

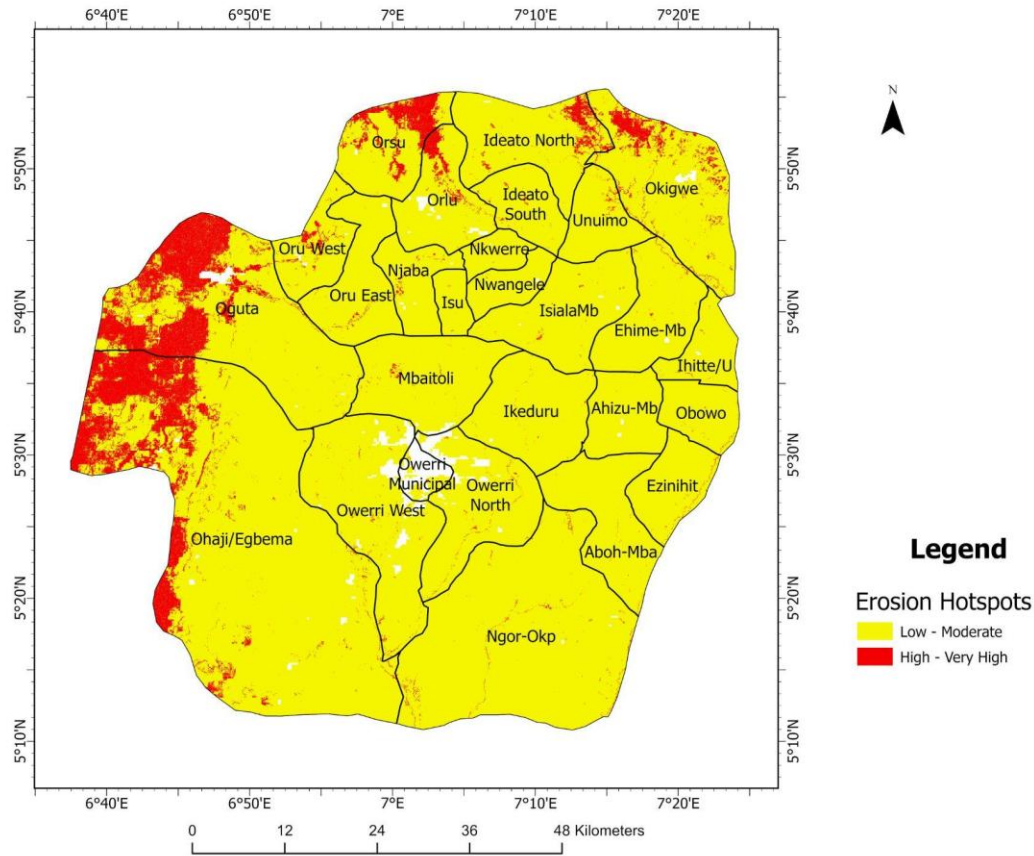


Figure 7b: Erosion Hotspot map

Table 7b: Erosion Hotspot LGAs in Imo State

Rank	LGA	Hotspot Area (km ²)
1	Oguta	21.42
2	Ohaji/Egbema	9.21
3	Orsu	1.89
4	Orlu	0.31
5	Ideato North	0.06
6	Okigwe	0.002

LGAs with dominant erosion hotspot concentration based on severity threshold analysis

4.7 Discussion

The level of erosivity of rainfall throughout Imo State is significantly high and this indicates the occurrence of heavy rainfall in the area that is as a result of the tropical humid climate. The spatial distribution indicates an evident rise of erosivity in the north of the state in the southern parts and southwestern areas where the highest values were observed. Such a gradient reflects previously known associations between the intensity of rainfall and the erosion potential as indicated by Huang et al. (2020) and Ziadat and Taimeh (2013). The small Cohen variation value achieved in this paper shows small spatial variation in erosivity and this implies that the effect of rainfall distribution is generally uniform throughout the state. The same trends have been noticed in southeastern Nigeria where the variability of interannual rainfall is usually low (Ezeh, 2023). Rainfall is therefore a potent erosive force, but it does not completely provide the explanation of the observed spatial variation of the intensity of erosion. The erodibility of the soil in Imo state is generally low, mainly because the silt content is rather low and the soil is also organic and specifically in the south areas. High levels of soil organic carbon (SOC) and soil organic matter (SOM) increase the stability of the aggregates and decrease the detachment, which is consistent with the studies by Keesstra et al. (2016) and Ostovari et al. (2022). Nevertheless, the rate of erosion in some of the LGAs in the south is high despite this inherent resistance. This paradox evidently puts into the limelight the importance of non-soil controls, such as slope and land cover. In alluvial soils, which are highly permeable in certain sections of the state, runoff is initially limited due to the high infiltration rate, however, field tests, and previous research indicate that once the alluvial soils become saturated with prolonged rainfall the soils become extremely vulnerable to erosion (Ezeh, 2023). The erosion risk is high at the very end of the rainy season and this is caused by this seasonal saturation effect. Topographic analysis shows that Imo State is controlled by low-relief terrain with more than 99 % of the territory occupied by slopes lower than 16deg. Slopes are lowest on the western and eastern sides of the major river systems, with moderately steep slopes being found in the central and southern uplands. The LS-factor distribution proves that slope length and steepness are very powerful factors in controlling the erosion patterns, as reported by Koirala et al. (2019) and Ayele et al. (2022). The LGAs that registered high LS values and the proportionate high rates of soil loss included Orlu, Orsu and Okuigwe. The floodplain LGAs like Aboh-Mbaise and Ngor-Okpala had low LS values and low intensity of erosion as another sign of protective slope, which is gentle. Dynamics in land use and land cover became a major source of variability in erosion. The value of the coefficient of variation

in the C-factor is large which depicts a great spatial heterogeneity in the vegetation cover and land management practices. The fast growth of urban areas, population increase and intensification of agriculture has dramatically decreased the natural vegetation especially in the southern LGAs like Owerri West, Ohaji/Egbema and Orlu. This trend is in line with the findings of Egbueri et al. (2022), who documented the prevalence of vegetation degradation in southeastern Nigeria. Forest and shrub cover though there are still found in isolated pockets and they are poorly distributed hence their use has a limited ability to cover the soil surfaces. Earlier research indicates that the rates of erosion are high in bare land, croplands, and built-in areas (Marondedze and Schutt, 2020; Ascencio-Sanchez et al., 2025), which can also be noticed in this research. The Figure below shows the spatial distribution of soil loss and reveals that most parts of the state have been affected by erosion, but the worst of it is in the LGAs that have recorded high rates of land transformation and medium and steep slopes. Naturally vegetated areas and floodplain environments tended to have fewer erosion rates, which validated the buffering effect of the plant cover as stated by Kidane et al. (2019). Nevertheless, this effect of protection decreases with the high intensity of rainfall and the rising slope as observed by Chen et al. (2018) and Ge et al. (2023). In Imo State, the thin and disrupted vegetation cover within the areas where the rainfall is high is not enough to counter the effects of the topography and surface runoff in the area and lead to the development of hotspots of erosion. Erosion rates in Imo State are closely linked to the regions of rather steep slopes and greater relief which confirms the conclusions made by Fagbohun et al. (2016), Huang et al. (2020), Merchan et al. (2023), Ziadat and Taimeh (2013), and Ezech et al. (2024). The A-factor analysis indicates that the soil erosion is mostly critical throughout the state. A relatively small number of LGAs had relatively low values of mean annual soil loss, whereas erosion rates were quite high in most LGAs. Maximum erosion rates were recorded in LGAs that had been upland and rapidly urbanised like Orlu, Orsu, Owerri West and parts of Okigwe as the mean values of soil loss were always high. Conversely, the floodplain LGAs such as Aboh-Mbaise and Ngor-Okpala showed relatively low rates of erosions because they were gently sloped and had good vegetation cover. The given time trend suggests that soil erosion rates have only been rising since 2017 to 2025 which is in line with the trend of the C-factor values, as they have steadily been on the rise during the same period. This tendency is a sign of the further degradation of the vegetation cover due to the urban growth, agricultural intensification and infrastructural development of the state. The statistically significant rise in the C-factor demonstrates that land cover change constitutes the

most important factor of the erosion processes in Imo State, which is more significant than the variability of rainfalls (Belay & Mengistu, 2021). These results support the importance of land management in erosion control and support comparable results in tropical settings (Chen et al., 2018; Ge et al., 2023). All in all, the paper has added weight to the existing information regarding the intricate relationship between topography, land cover, and climatic variables in the control of erosion processes. Combining multi-temporal data into a Google Earth Engine framework, the study offers a versatile and scalable system of erosion dynamics observation and prioritized areas of intervention. The paper builds on the research of Ezech et al. (2025) as it proves the efficiency of a Google Earth Engine-based model in spatiotemporal erosion modelling and provides a solid scientific foundation of the erosion mitigation planning in Imo State.

5.0 Conclusion

This paper used the RUSLE model in the Google Earth Engine setting to measure the spatial and temporal change of soil erosion in Imo State. The findings prove that soil erosion is not evenly spread, as acute erosion is concentrated in particular LGAs, in particular, in Ohaji/Egbema and Oguta, and only a few LGAs have a comparably low risk of erosion. Despite the fact that the large areas of the state belong to the classes of low to moderate erosion, the area of high to severe erosion is significant and poses a threat to the environment as well. The results show that the dynamics of C-factor and LS-factor are the main factors that determine the spatial variability in erosion as they show the high impact of land cover change and topography. Conversely, rainfall erosivity and soil erodibility were less spatially variable. This validates the presence of vegetation degradation, urban growth and slope features as the prevailing factors that determine erosion in Imo State. The efficiency of the RUSLE model combined with a cloud-based analysis shows that it is applicable to the assessment of erosion and decision support on a regional scale. The study will also be very beneficial to the erosion research and documentation especially in the southeastern part of Nigeria and will be a good reference to the Institute of Erosion Studies, FUTOWA archive library, and to academics in future studies relating to land degradation. On the basis of these results, sustainable land management techniques reforestation, agro forestry, and conservation agriculture are to be actually encouraged. Intervention by the government must more than just be structural gully control but involve nature based intervention to address rill and sheet erosion. Redevelopment of erosion control programmes such as those of similar effort such as NEWMAP is highly suggested to make sure of long-term stability in the landscape and environmental sustainability in Imo State.

Declarations**Ethical Approval**

Not applicable. This study did not involve human participants, animals, clinical trials, or sensitive personal data.

Consent to Participate

Not applicable.

Consent to Publish

Not applicable.

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Declaration of the Use of AI in the Writing Process

The authors declare that no generative AI or AI-assisted tools were used in the generation of data, analysis, or interpretation of results. Generative AI tools were employed solely to support language refinement, editing, and formatting of the manuscript. All scientific content, interpretations, and conclusions are entirely the work of the authors.

Data Availability

All datasets used in this study, including CHIRPS rainfall, SoilGrids soil properties, SRTM DEM, and ESRI Global Land Use/Land Cover data, are publicly accessible through the Google Earth Engine Data Catalog at <https://developers.google.com/earth-engine/datasets>.

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