Using Machine Learning and GIS to Monitor Sandbars along the RiverNiger in the Niger Delta, Nigeria

Abstract:

The use of GIS and machine learning techniques to map sand bars along the Niger River in the Niger Delta, Nigeria, spanning the period from 1974 to 2024. It integrates DEM, Landsat series satellite imagery obtained from the USGS. Rainfall data from 1983 to 2023, sourced from the Center for Hydrometeorology and Remote Sensing, supplements the analysis. Object-Based Image Analysis is employed to identify and map sand bars, while Support Vector Machines automate classification to ensure precision and recall metrics. ArcGIS 10.5 tracks temporal changes, revealing significant morphological shifts influenced by both natural processes and human activities. Results show a significant reduction in sandbar length from 1.6502 km in 1974 to a low of 0.7437 km in 2004, while sandbar area decreased by 68% to 0.0587 km² by 2004 before partially recovering to 0.1271 km² in 2024. Key parameters such as Aspect Ratio (AR) and Elongation Ratio (ER) demonstrate relative stability, indicating consistent directional flow influence on sandbar shape. Spatial autocorrelation analysis (Moran's Index of 0.138562) links sandbar dynamics to elevation, with a significant correlation between rainfall and sandbar area fluctuations ($R^2 = 0.7576$). Regression analysis reveals strong associations among sandbar length, width, and area (R^2 values up to 0.9737), indicating predictable morphometric responses to environmental changes. Additionally, grain size impacts sandbar stability, with medium to coarse sands forming more stable structures. Comparative global analyses reinforce the broader implications of these findings for sustainable river management, stressing the need for balanced policies in response to climate change, sediment transport, and anthropogenic activities. The study underscores the importance of advanced monitoring technologies for effective riverine ecosystem management and sediment regulation

Keywords: Sandbars, River Niger, geomorphology, sediment dynamics, remote sensing, Machine learning, climate variability

INTRODUCTION

The Niger River, Africa's third-longest, flows through multiple countries before reaching the Atlantic Ocean via Nigeria Niger Delta[1].This region is renowned for its intricate network of rivers, creeks, and sandbars, which play a crucial role in hydrodynamics and sediment transport [2]. Monitoring these sandbars is essential for understanding sediment patterns, navigation safety, ecological health, and managing coastal erosion and flooding risks.Recent advancements in machine learning have significantly bolstered Geographic Information Systems (GIS) capabilities in environmental monitoring. Machine learning algorithms can efficiently process vast datasets, discern patterns, and predict future changes with high precision. These techniques are particularly valuable for studying the dynamic formation and erosion of sandbars [3].Recent studies underscore GIS's transformative impact on spatial analysis and sandbar monitoring in the Niger Delta [4], [5]. GIS technologies integrate satellite imagery, aerial surveys, and ground-based data to create detailed maps and models of sandbar distribution and morphology. This integration supports comprehensive spatial analyses, enabling researchers to assess changes in sandbar extent, shape, and connectivity in response to environmental factors such as river flow and sediment transport[3].Furthermore, machine learning is increasingly used for predictive modeling and trend analysis in sandbar monitoring. Recent research highlights its application in predicting sandbar evolution based on historical data and environmental variables [6], [7]. These models improve our ability to forecast changes in sandbar morphology and distribution under different scenarios, aiding proactive management strategies to mitigate erosion and sedimentation in deltaic ecosystems.Collaborative efforts among researchers, government agencies, and local stakeholders have been pivotal in advancing sandbar monitoring in the Niger Delta. Interdisciplinary approaches integrating hydrology, geomorphology, ecology, and remote sensing have led to innovative methodologies and decision-support systems. This collaborative framework supports adaptive management strategies that balance conservation goals with socioeconomic development imperatives in the region.The evolution of sandbar monitoring from 1974 to 2024 reflects a progression towards more integrated and technologically advanced approaches. Recent advancements in remote sensing techniques have enhanced the spatial and temporal resolution of data, improving mapping accuracy and monitoring efforts [8], [9],[3]. By combining remote sensing data with ground-truthing techniques, researchers validate and calibrate predictive models, enhancing monitoring frameworks' reliability and applicability [10],[11].Looking ahead, enhancing data accessibility, improving predictive capabilities, and fostering stakeholder engagement will drive the future of sandbar monitoring in the Niger Delta. Real-time monitoring systems and interactive GIS platforms hold promise for facilitating timely decision-making and adaptive management in response to environmental changes. Continued collaboration among researchers, policymakers, and local communities will be essential to address emerging challenges and sustain the ecological integrity of sandbars and associated ecosystems in the Niger Delta. Therefore, this researchaim at monitoring of sandbars in the River Niger over a 50-year period (1974-2024) using GIS and Machine learning. By analyzing historical and contemporary satellite imagery, the project aims to gain a deeper understanding of sandbar dynamics and their response to environmental and anthropogenic pressures

STUDY AND GEOLOGY OF THE AREA

This study examines a specific section of the Lower Niger River, flowing through Anambra, Delta, and Bayelsa States in Nigeria (Latitudes: 5°20'00" N - 5°53'30" N; Longitudes: 6°32'30" E - 6°43'30" E), as shown in Figure 1. Geologically, this region is part of the Niger Delta basin's freshwater geomorphic unit [12]. The area is accessible via the East-West major road and minor village roads, with creeks and tributaries connecting it to the Atlantic Ocean. The specific study area within the Niger Delta basin has a subsurface geology consisting of three primaries. Tertiary lithostratigraphic units: TheAkata, Agbada, and Benin Formations, capped by Quaternary sediments with diverse characteristics [13]. These formations, arranged from deepest to shallowest, indicate a gradual environmental transition from marine to deltaic, and finally to fluvial settings, reflecting a trend of coarsening sediment deposition over time [13][14]. The uppermost Benin Formation is crucial for the region water resources, acting as the main water-bearing unit within the Niger Delta basin. Clay layers interspersed within the Benin Formation create a multi-layered aquifer system, with the shallowest unconfined aquifer lying at depths of about 20 to 40 meters [15][12][16].

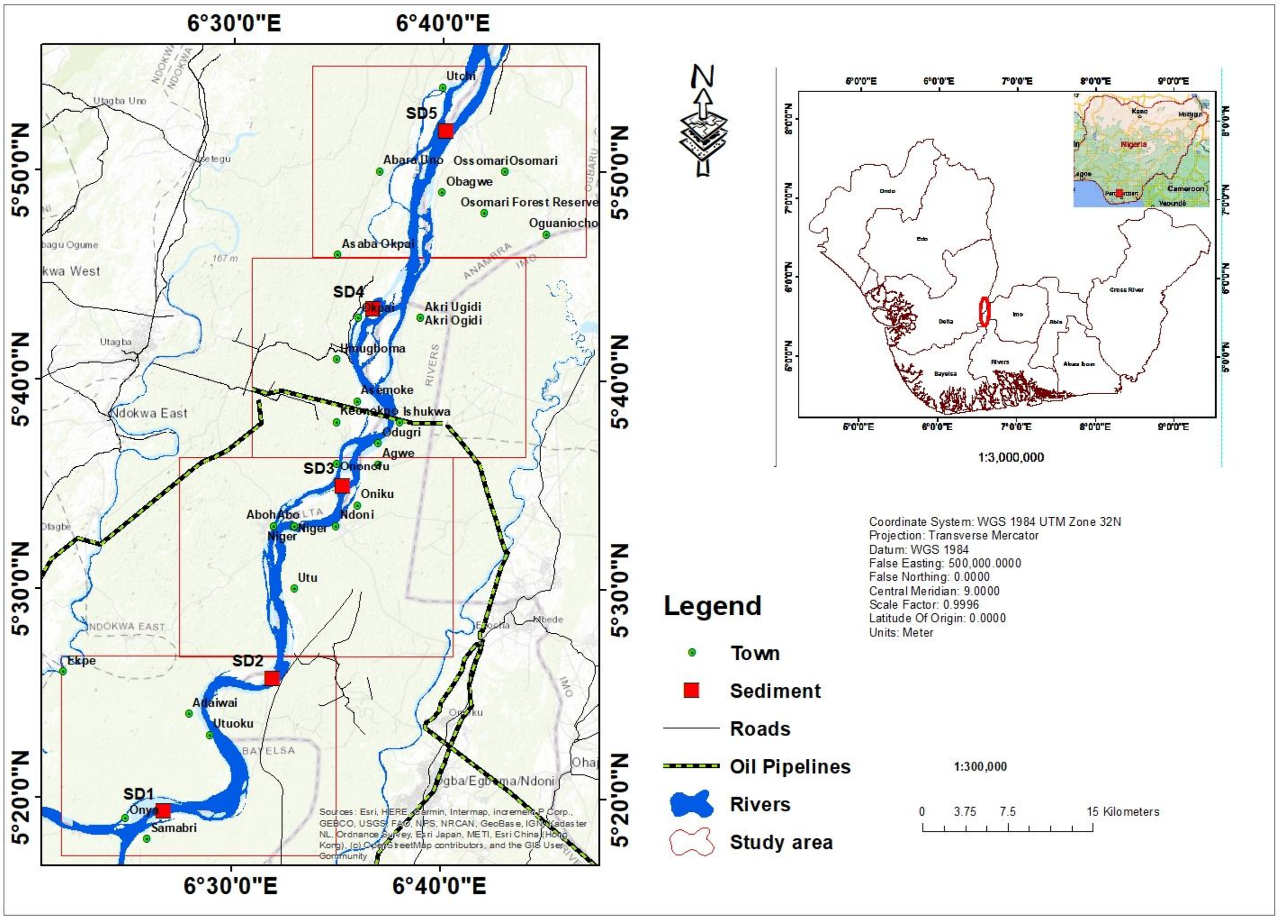

Figure 1: Study area map.

METHODOLOGY

The combination of multi-decadal data from various sources establishes a robust foundation for investigating the morphodynamic evolution (changes in shape and movement) of the River Niger sandbars over the 1974-2024 timeframe.

Figure 2a: Google Earth image of 2024 showing sand bars along River Niger in Niger Delta region

Data Collection

Remote Sensing Data:

- **Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM):** The foundation of the elevation data came from the SRTM DEM, retrieved from the EarthExplorer platform offered by the United States Geological Survey (USGS) https://earthexplorer.usgs.gov/.
- **Landsat Imagery:** The Landsat satellite series provided the primary source of imagery for the study. This selection offered a comprehensive historical record to monitor changes within the designated area. Data from various Landsat missions (Landsat 1, 4, 5, 7, and 8) from 1974 to 2024 were specifically chosen to ensure consistent path-row coverage (Path 189, Row 56) and a high spatial resolution of 30 meters. Landsat data was also obtained from the USGS EarthExplorer platform https://earthexplorer.usgs.gov/.

Additional Data:

- **Rainfall Data (1983-2023):** Rainfall data spanning 1983 to 2023 was incorporated into the analysis. This data was acquired from the Center for Hydrometeorology and Remote Sensing

(CHRS) https://chrs.web.uci.edu/. The inclusion of rainfall data acknowledges the established research on the influence of precipitation on river morphology [17] -[23].

- **Sediment Samples:** Six sediment samples were collected directly from the sandbar area along River Niger and send to laboratory for analysis. Sieve analysis was conducted on the samples to understand the textural properties of the sandbar material.

Methods

Sand Bar Identification and Mapping

To identify and map sand bars along the Niger River, an Object-Based Image Analysis (OBIA) technique is utilized. This method segments and classifies sand bars in satellite imagery (Figure 2a) by examining their spectral characteristics, texture, and spatial relationships with the river channel using ArcGIS 10.5 and python program. The process can be broken down as follows (Figure 2b):

Sand Bar Change Analysis

Once the sand bars are identified and mapped, their morphological characteristics are analyzed over time. Key features such as perimeter (L) and Shape Area (A), are extracted using ArcGIS 10.5. These features are calculated as follows:

Satellite images are divided into distinct areas based on similarities in color and texture. This process uses a technique called multi-resolution segmentation[24].The goal is to accurately identify sand bars by creating segments that are the right size, shape, and compactness

$$\text{Segmentation} = f(\text{scale}, \text{shape}, \text{compactness}, \text{spectral homogeneity}, \text{spatial homogeneity}) \quad \text{(Eq.1)}$$

Where:

- Scale is the parameter controlling the size of the segmented objects.
- Shape and compactness control the geometric properties of the segmented objects.
- Spectral homogeneity and spatial homogeneity ensure that the pixels within each segmented object are similar in spectral and spatial terms.

Classification

To distinguish between sand bar and non-sand bar areas within segmented regions, a rule-based system is employed. This system analyzes spectral properties (like light reflection), textural characteristics (such as image contrast and smoothness), and the location relative to the river channel to make its classifications [25].

$$\text{Classify } (R_i) = \begin{cases} SandBar & if R i satisfies rules \\ Non - SandBar & otherwise \end{cases} \text{(Eq.2)}$$

Where *Ri*is the *i*-th segmented region and the rules include:

- Spectral characteristics: reflectance values
- Texture measures: contrast, homogeneity
- Spatial relationships: proximity to the river channel

Spectral Analysis: Spectral indices sensitive to water and sand is employed to differentiate between sandbars, water, and surrounding land cover using Normalized Difference Vegetation Index (NDVI) [26].

$$\text{NDWI:} \frac{(NIR - R)}{(NIR + R)} \text{ (Eq.3)}$$

Where:

red (R) and near-infrared (NIR)

Machine Learning Automation: To streamline the process of identifying sandbars, researchers utilized Support Vector Machines (SVMs). They trained the SVM model using manually digitized sandbar data. Once trained, the model was able to recognize the characteristics of sandbars and automatically categorize all sandbar data from the study period [27] [28]. The accuracy of this automated classification was evaluated using a confusion matrix and metrics like precision, recall, and F1 score.

Training SVM:

Train SVM (training data) =SVM Model

Where training data includes manually digitized sand bars with their spectral, texture, and spatial features.

Classification using SVM:

$$\text{Classify }(R_i) = \begin{cases} Sand\ Bar & if\ SVM\ Model\ (Ri) = \text{Sand } bar \\ Non - Sand\ Bar & otherwise \end{cases} \quad \text{(Eq.4)}$$

Accuracy Assessment:

$$\text{Confusion Matrix}=\begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix} \quad \text{(Eq.5)}$$

$$Precious = \frac{TP}{TP+FP} \quad (Eq.6)$$

$$Recall = \frac{TP}{TP+FP} \quad \text{(Eq.7)}$$

$$\text{Recall} = 2 * \frac{\text{Precious}*\text{Recall}}{\text{Precious}+\text{Recall}} \quad \text{(Eq.8)}$$

Where:

- TP = True Positives
- FN = False Negatives
- FP = False Positives
- TN = True Negatives

Machine Learning for Driving Factors Analysis

Feature Extraction: Rainfall data and elevation data are extracted and pre-processed. Spatial autocorrelation techniques are applied to understand the spatial dependency of sand bar changes on these factors.

1. **Feature Extraction**:

   Extract and preprocess rainfall data (R) and elevation data (*E*).

   Apply spatial autocorrelation techniques to understand spatial dependency of Sand bar changes (*S*).

2. **Model Development**:

   Various regression models (linear regression,) are trained using the extracted features. The models are assessed using correlation coefficients to determine the strength of relationships.

   Train regression models (linear regression) to relate Sand bar changes (*S*) to rainfall (*R)* and elevation (*E*).

   Use correlation coefficients to assess model performance.

   The equation for a linear regression model can be written as:

$S=\beta_0+\beta_1 R+\beta_2 E+\epsilon$ (Eq.9)

Where:

- S = Sand bar changes
- R = Rainfall data
- E = Elevation data
- β_0,β_1,β_2 = Regression coefficients

- ϵ = Error term

Spatial autocorrelation can be assessed using Moran's I [29]

$$\text{Moran's I} = \frac{\mathrm{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\omega ij\,(xi-x)(xi-x)}{\sum_{i=1}^{N}(xi-x)^2)\sum_{i=1}^{N}\sum_{j=1}^{N}\omega ij} \text{(Eq.10)}$$

where:

- N is the number of observations,
- x_i, x_j are the values of the variable at locations *i* and *j*,
- x is the mean of the variable,
- ωij are the spatial weights between locations *i* and *j*.

The Pearson correlation coefficient is calculated using the following formula[30]:

$$r = \frac{\mathrm{Cov(x,y)}}{(\mathrm{sd(x)} * \mathrm{sd(y)})} \text{(Eq.11)}$$

Where:

- r is the Pearson correlation coefficient
- Cov(x, y) is the covariance of the two variables x and y
- sd(x) is the standard deviation of the variable x
- sd(y) is the standard deviation of the variable y

Analyze the difference in means using:

Difference means = X_1-X_2 (Eq.12)

Where:

X_1, X_2 are the means of two different samples or groups.

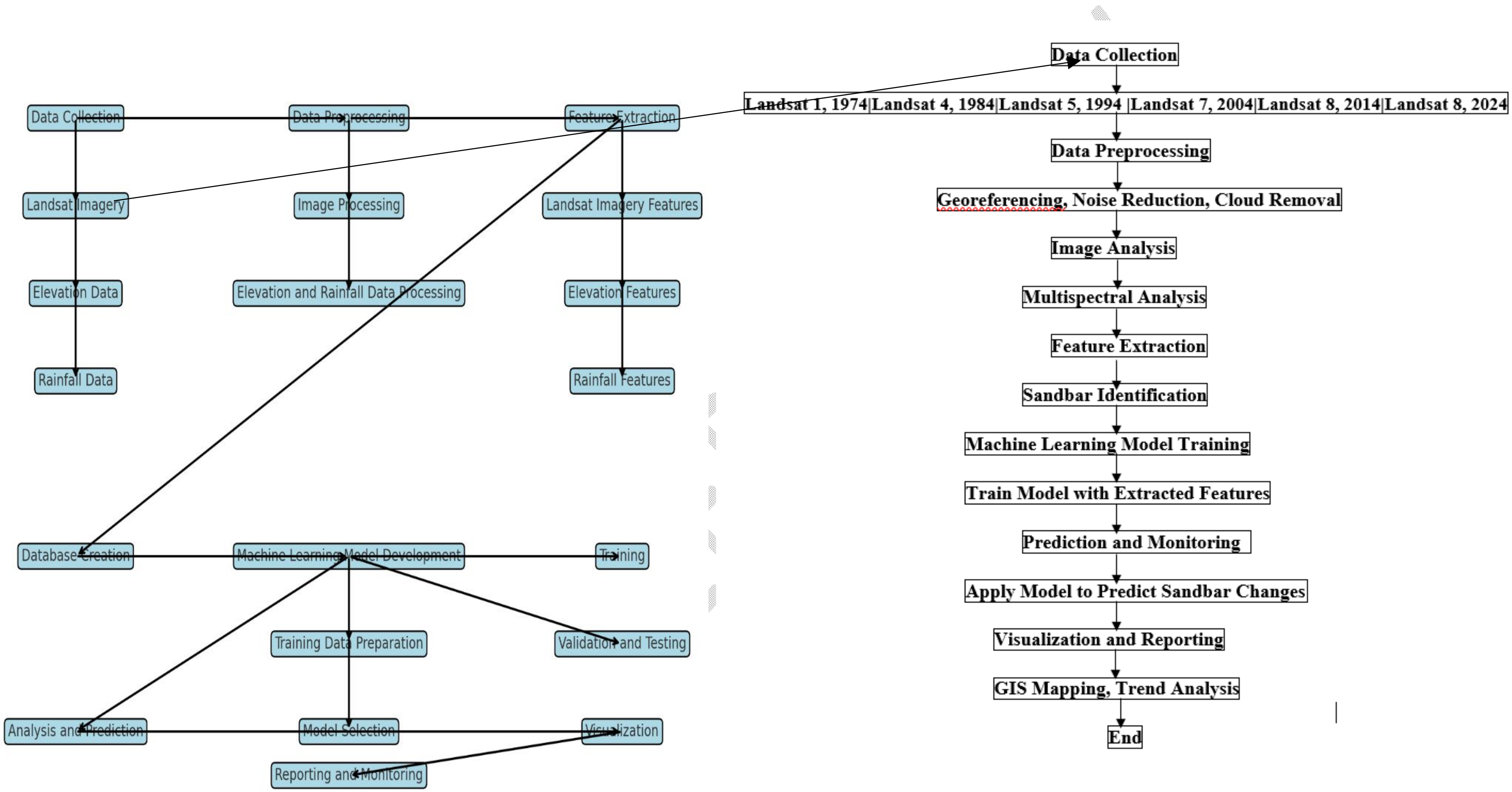

Figure 2b: Flow chart procedure

RESULT AND DISCUSSION

RESULTS

Figure 3 presents satellite images showing the River Niger and its sandbars from 1984 to 2024. These images illustrate the temporal changes in the river morphology and the spatial distribution of sandbars. The use of remote sensing technology has enabled the continuous monitoring of these features, offering a comprehensive view of their evolution over time.

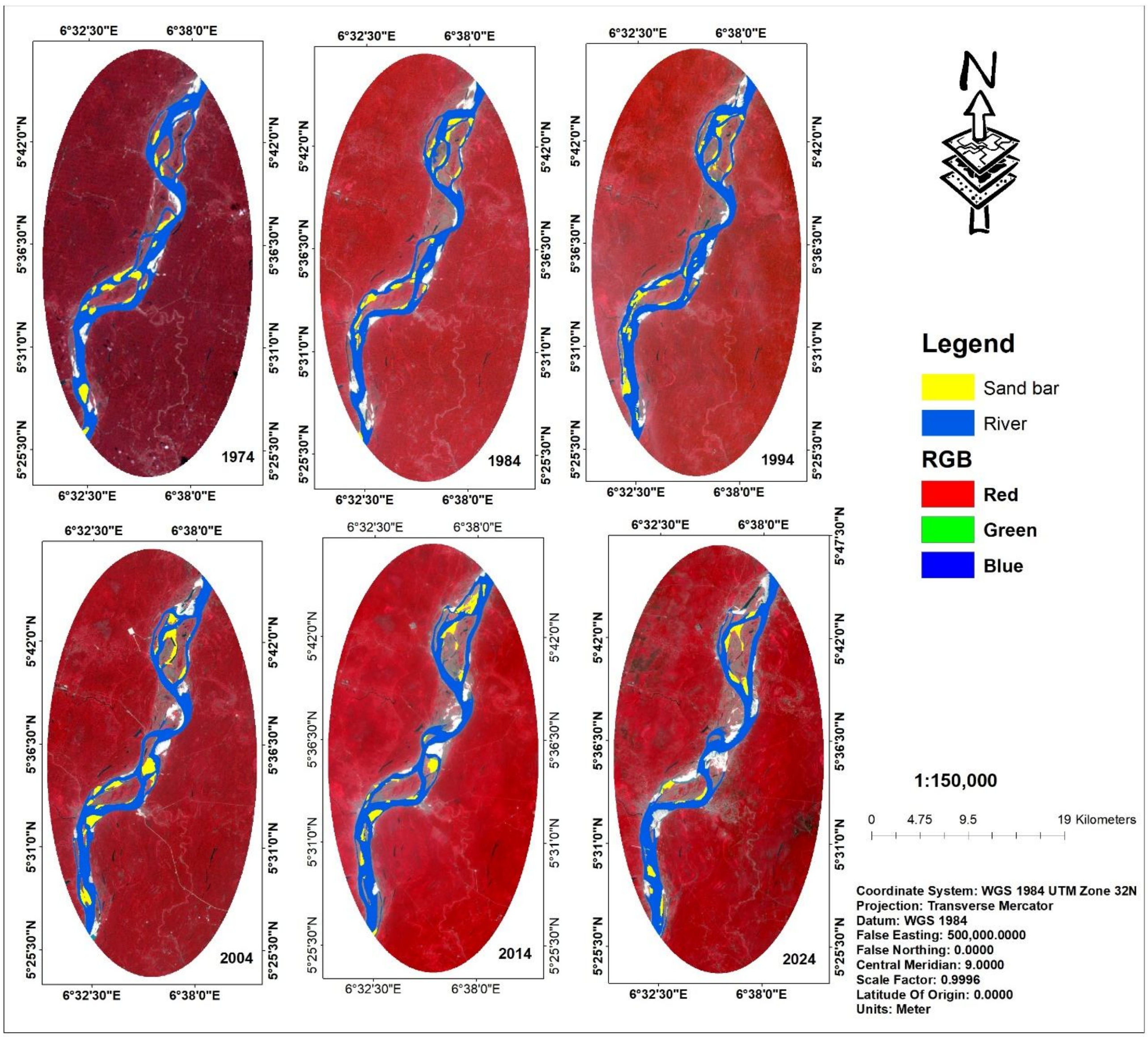

Figure 3: Satellite images showing River and Sand bar from 1984-2024.

The Niger Delta is a complex and sensitive ecosystem influenced by riverine processes and sediment dynamics. Sandbars, as transient features along the Niger River, are constantly shaped by hydrological forces, sediment transport, and potentially anthropogenic factors. Table 1 encapsulates these changes over a fifty-year period (1974-2024). These analyses are vital for understanding sandbar stability, ecosystem dynamics, flood risk management, and conservation efforts in the region.

Table 1: Sandbar Parameters Over Time (1974-2024)

Parameter	1974	1984	1994	2004	2014	2024
Length (L) km	1.6502	1.3544	1.042	0.7437	1.3389	1.3183
Area (A) km²	0.185	0.107	0.08	0.0587	0.1297	0.1271
Width (W) km	0.0636	0.0487	0.036	0.0228	0.0443	0.0445
Perimeter (P) km	3.4276	2.8063	2.155	1.5331	2.7664	2.7256
River Area (km²)	46376.54	42711.05	48506.25	46008.32	49601.2	44796.47
Aspect Ratio (AR)	24.9863	25.9256	25.172	24.0168	25.8828	25.2423
Elongation Ratio (ER)	4.9639	5.0343	4.972	4.8318	4.9807	4.9738
Circularity (C)	0.1214	0.1203	0.122	0.1287	0.1255	0.1226
Compactness (Com)	0.4833	0.3957	0.304	0.2162	0.3901	0.3844
Form Factor (FF)	0.0421	0.0417	0.042	0.0448	0.0437	0.0426

DISCUSSION

Sandbar Characteristics and Trend Analysis

In Table 1, key sandbar parameters over five decades reveal a significant evolution in geometric and shape-based aspects, reflecting the influence of natural and anthropogenic factors on sandbar morphology. Monitoring sandbars using GIS and Machine Learning (ML) has made it possible to detect changes over time with high precision. Research indicates that river morphology is influenced by sediment transport, hydrological events, and climate change [31-32], all of which affect the Niger River's sandbars.

Geometric Parameters

From 1974 to 2024, the sandbar's physical dimensions have changed notable as seen in Table 1. The length decreased from 1.6502 km in 1974 to 1.042 km in 1994, hitting a low of 0.7437 km in 2004 from Figure 4. These reductions suggest erosion or sediment redistribution, possibly linked to hydrological changes or upstream interventions [33]. The sandbar area also declined from 0.185 km² in 1974 to 0.0587 km² in 2004, signaling a 68% decrease, before recovering slightly to 0.1271 km² by 2024. Such fluctuations indicate that sandbar morphology is not static; instead, it is responsive to both natural processes and external interventions [34-35]. Studies by Naciri et al., [36]and Lawsonet al., [37] highlight similar trends in river systems, where sandbar size decreases as erosion outpaces sediment deposition, often due to changes in river discharge or sediment availability. Moreover, periodic increases in sandbar size post-2004 suggest that sediment availability may have increased or that hydrological regimes have altered to favor deposition in the Niger Delta.

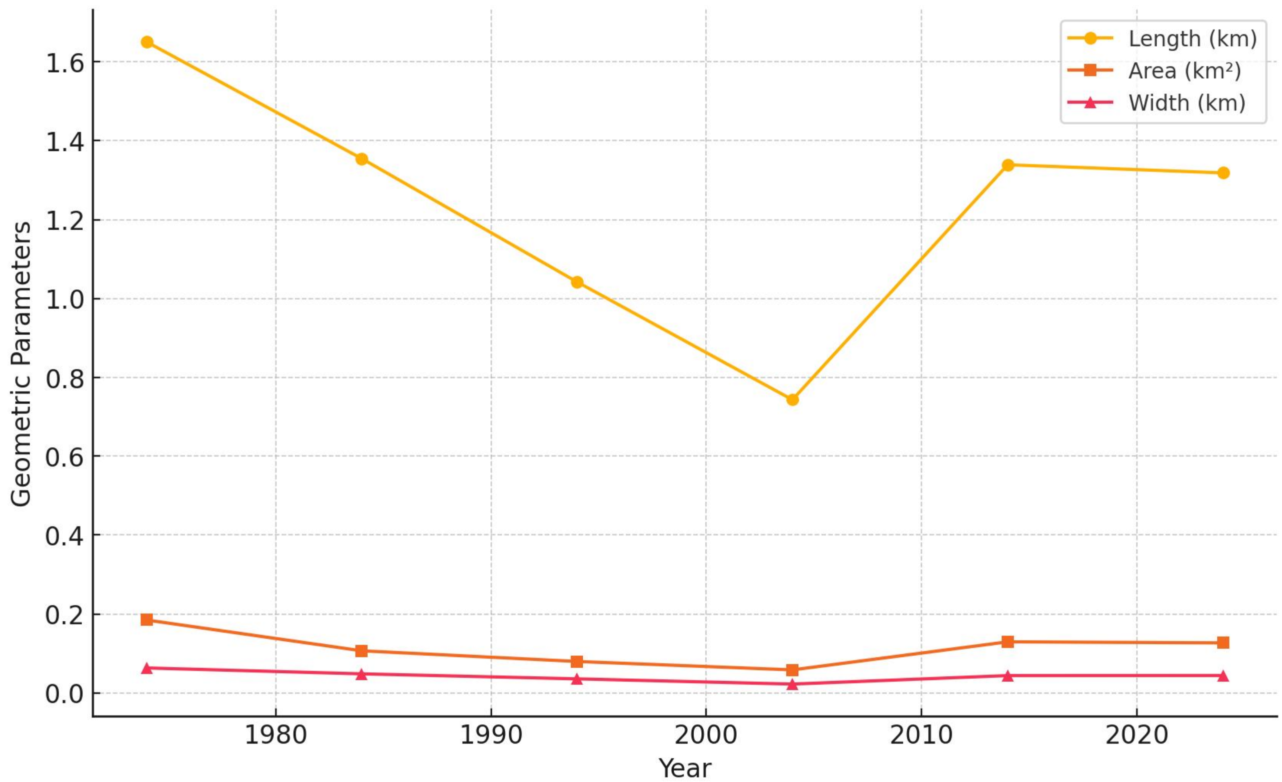

Figure 4: Geometric parameters of Sand bar from 1984-2024.

Perimeter

Table 1 shows changes in perimeter values over time, with a steady decrease from 3.4276 km in 1974 to 1.5331 km in 2004, followed by a slight increase to 2.7256 km by 2024. This reduction in perimeter mirrors the overall decrease in area and length, indicating that the sandbar has become geometrically less complex. Such changes in perimeter are linked to sediment erosion and hydraulic processes that reshape the sandbar into simpler forms over time. Perimeter variations are important for understanding the degree of sandbar fragmentation and erosion, which affect how the sandbar interacts with river flow.

River Area and Comparative Metrics

The River Area (km^2) parameter provides context for sandbar changes within the broader Niger River system. Observing the river's total area over time, we see fluctuations that correlate with periods of sandbar shrinkage or expansion. For instance, a decrease in river area from 46376.54 km^2 in 1974 to 42711.05 km^2 in 1984 in Figure 5 aligns with initial sandbar reductions, potentially due to lower water volumes or sediment flow. Similarly, as the river area increased by 2014, so did the sandbar area, shows a link between river conditions and sandbar formation [38-39]. Understanding these patterns within a larger river context helps researchers and stakeholders anticipate changes to river dynamics that could affect surrounding ecosystems and communities.

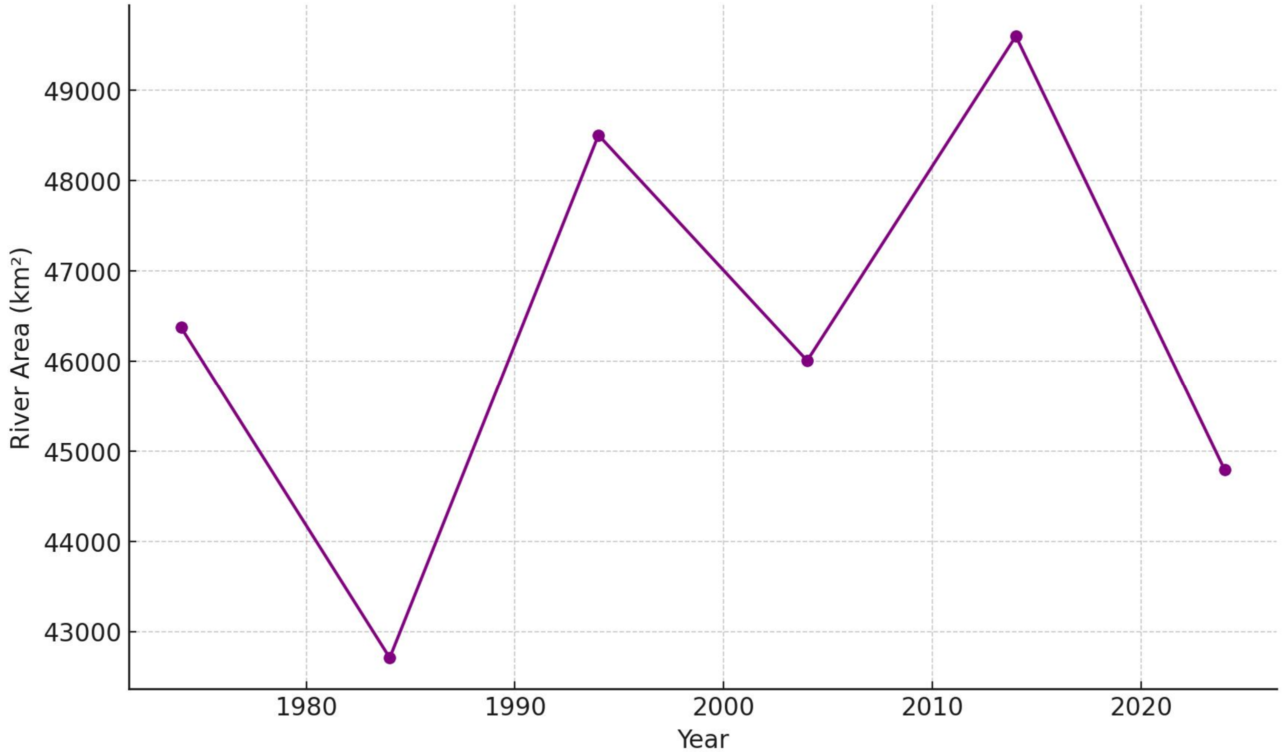

Figure 5: River area over time 1984-2024.

Shape-Based Parameters

Shape-based parameters, such as the Aspect Ratio (AR), Elongation Ratio (ER), Circularity (C), Compactness (Com), and Form Factor (FF), are crucial for describing sandbar morphology. Analyzing these indices offers a deeper understanding of sandbar shape stability and transformation over time in Table 1.

Aspect Ratio (AR): The aspect ratio remained relatively consistent over time, fluctuating slightly between 24.0168 and 25.9256 (Figure 6). This stability in AR reflects the sandbar's consistent elongation pattern despite changes in its overall size. Studies on sandbar morphology, such as Kuanget al., [40]indicates that consistent aspect ratios indicate a stable flow environment, as elongation is maintained by consistent current direction.

Elongation Ratio (ER): Similar to the AR, the elongation ratio remained nearly constant over the years, with values between 4.8318 and 5.0343 in Figure 4 and Table 1. This suggests that sandbar shape has not deviated significantly from an elongated form, despite reductions in length and width.

Such stability could indicate a steady hydrological regime, as elongation ratios are typically influenced by the directional flow of water that shapes the sandbar over time [41-42].

Circularity (C) and Compactness (Com): Circularity values stayed within a narrow range (0.1214 to 0.1287) in Table 1 and Figure 6, while compactness showed slight declines over time, pointing to an elongated sandbar form with less rounded edges. Lower circularity and compactness imply irregular shapes and support findings that sandbars in dynamic environments like the Niger Delta tend to be elongated rather than compact, due to frequent erosion and deposition events [43-44]. Compactness reductions may indicate sediment loss from the sandbar's outer sections, a phenomenon often observed in riverine environments undergoing morphological change [45].

Form Factor (FF): The form factor (FF) values in Table 1 remained stable, with minor variations. FF provides insight into the sandbar's elongation by comparing its area to the square of its perimeter. A consistent FF indicates that sandbar shape is resilient to size changes, likely due to balanced hydrological forces 46].

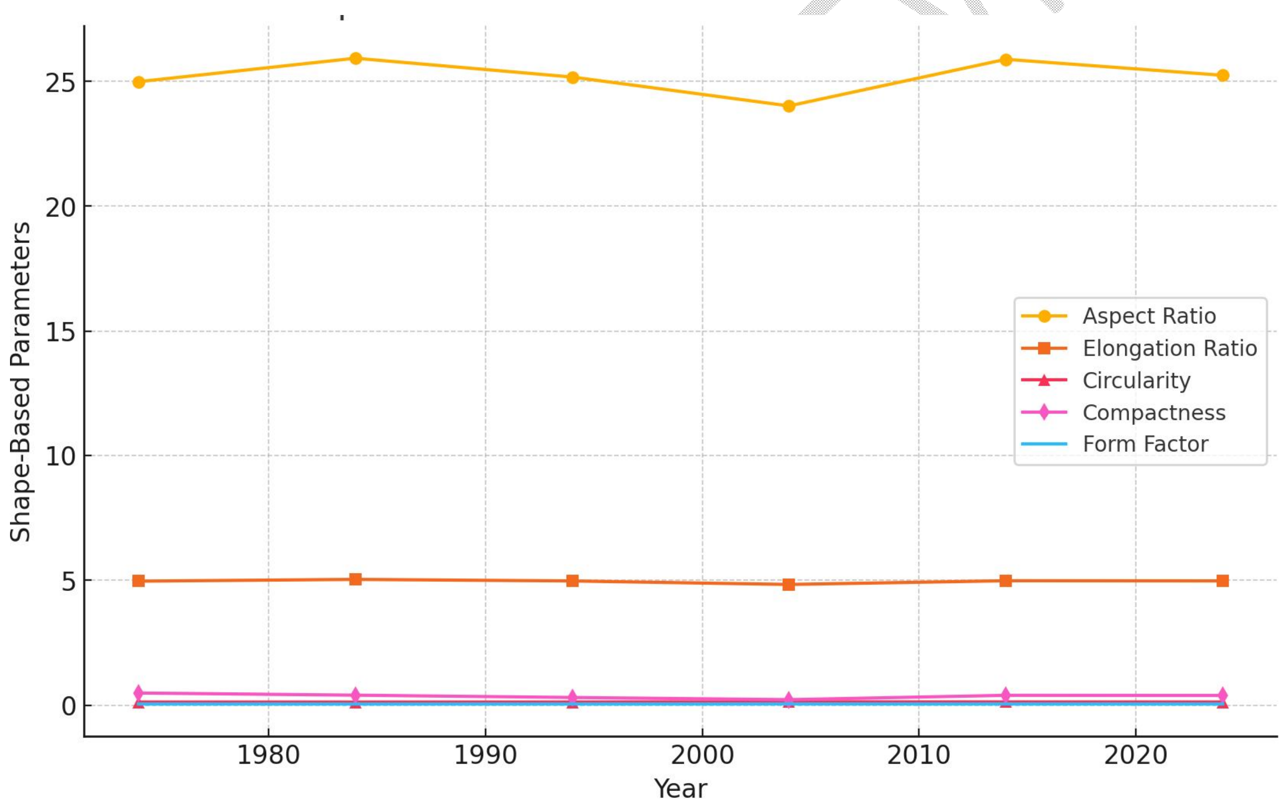

Figure 6: Shape- Based parameters of Sand bar from 1984-2024.

Long-term Trends in Sandbar Dynamics

The long-term trends revealed in Table 1 show sandbar shrinkage from 1974 to 2004, followed by partial recovery. These shifts may reflect climatic events, sediment supply variations, and human interventions, such as dam construction or dredging upstream. Reduced sandbar dimensions from 1974 to 2004 could be a consequence of sediment starvation or increased erosion, as suggested by Jana et al., [47]and Liuet al., [46]. Long-term trends provide essential insights into how sandbars respond to environmental and human-induced pressures, influencing policies for river management and sediment regulation. In recent years, GIS and machine learning methods have advanced sandbar monitoring. Studies by Janušaitė et al., [48]; Taveneauet al., [39]; Lee et al., [49]indicate that these technologies allow for accurate monitoring of sandbar trends, capturing subtle changes in size and shape that could otherwise be missed. Such advancements enhance our understanding of sandbar resilience and their role within larger river ecosystems, supporting sustainable management.

Sandbar Expansion and Fluctuations

Examining sandbar area fluctuations provides valuable insights into sediment dynamics and riverine stability. Table 1 highlights a significant decrease in sandbar area from 1974 to 2004, followed by gradual expansion. Fluctuations in area reflect the combined influence of river discharge, sediment load, and local hydrodynamics. The recovery of sandbar area in recent years (up to 2024) may indicate improved sediment deposition conditions, perhaps due to changes in river flow or seasonal flooding patterns. Studies by Sweeney et al., [50]confirm that sandbar expansion often follows periods of sediment replenishment, which can be triggered by natural events such as seasonal floods or anthropogenic changes to river flow management.

Morphological Characteristics and

The morphological characteristics of the sandbar, as shown by shape indices like circularity, compactness, and aspect ratios, help to understand how sandbars evolve over time. The consistency of shape-based parameters such as AR and ER over time suggests a relatively stable sandbar morphology, despite size fluctuations. Research by Miselis, et al., [51]and Ferreira et al., [52]suggests that consistent shape metrics often indicate a balance between deposition and erosion forces, highlighting the resilience of sandbars to external influences.

Recent Trends (2004-2024)

The period following 2004 exhibits a trend towards stabilization in sandbar areas, with minor fluctuations observed (Table 1). This relative stability could be interpreted in a few ways. It's possible that the system has reached a state of equilibrium, where sediment input and removal are balanced, resulting in minimal changes in sandbar size. Alternatively, the stabilizing trend might reflect a dampening of the earlier fluctuations due to natural adjustments within the river system, such as the development of a new channel morphology that promotes sandbar stability [53].

However, the recent data from 2024 holds a layer of intrigue. While the maximum sandbar size appears to have decreased slightly compared to 2004, the mean sandbar area shows an increase (Table 1). This indicate a potential redistribution of sediment within the river system. Perhaps larger sandbars are being eroded and the resulting sediment is contributing to the formation of smaller, more numerous sandbars. This highlights the dynamic nature of sandbars, where erosion in one location can fuel deposition elsewhere.

Spatial autocorrelation analysis

Spatial autocorrelation analysis is a valuable tool in geographic research, revealing patterns of similarity or dissimilarity between neighboring locations. In the study of sandbars along the River Niger in the Niger Delta, Table 2 presents the results of global Moran’s Index analysis. The computed Moran's Index of 0.138562 indicates a positive spatial autocorrelation among sandbar characteristics and elevation, indicate that areas with similar elevations tend to exhibit similar sandbar dynamics. This finding is supported by a high Z-score of 12.295975 and a significant p-value of 0, indicating strong evidence against the null hypothesis of spatial randomness

Table 2: Spatial autocorrelation result between Sand bar and elevation in River Niger, in Niger Delta

Global Moran’s	Summary
Moran's Index	0.138562
Expected Index	-0.002045
Variance	0.000131
Z-Score	12.295975
p-value	0

Relationships between sandbar dynamics and rainfall patterns

Furthermore, Table 3 details the statistical analysis of rainfall patterns across Nigeria from 1983 to 2023. The data shows variability in annual rainfall, with a minimum of 1008.91 mm, a maximum of 1400.72 mm, and a mean of 1241.64 mm. The distribution is shownin Figure 7, which visually depicts the fluctuation of rainfall over the years, emphasizing the climatic variability that influences environmental processes such as sandbar formation and erosion dynamics [17]-[23].

The correlation analysis in Figure 8 further underscores the relationship between rainfall and sandbar dynamics, revealing a strong correlation coefficient ($R^2 = 0.7576$). This indicates that variations in rainfall significantly explain the changes observed in sandbar characteristics along the River Niger, highlighting the interconnectedness of climatic factors and geomorphological processes in riverine environments [17]-[23]. Therefore, these findings underscore the importance of spatial autocorrelation and climatic variability in understanding landscape dynamics and planning sustainable management strategies for riverine ecosystems.

Table 3: Statistical analysis of Rainfall from 1983-2023) across Nigeria

Parameter	**Rainfall (mm)**
Min	1008.91
Max	1400.72
Mean	1241.64
Median	1251.41
25th Percentile	1188.72
50th Percentile (Median)	1251.41
75th Percentile	1315.64

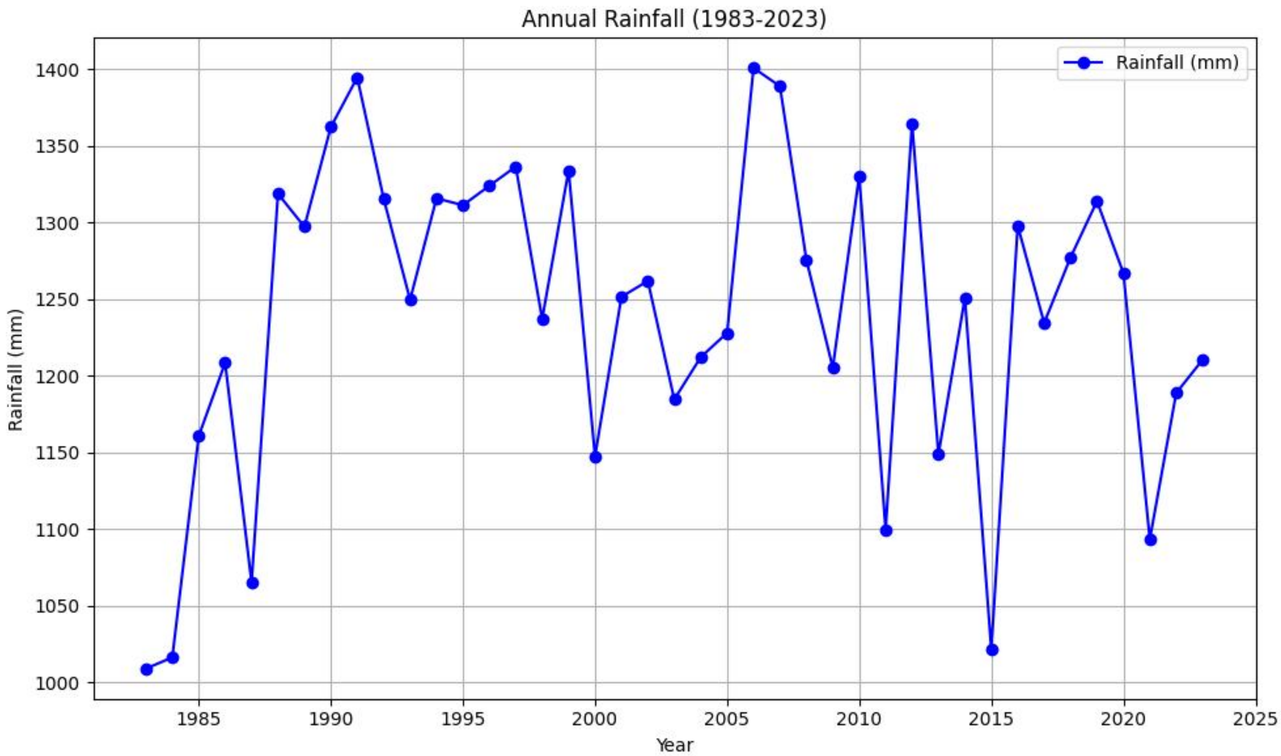

Figure 7: Graphical presentation of rainfall data Across Nigeria from 1983-2023

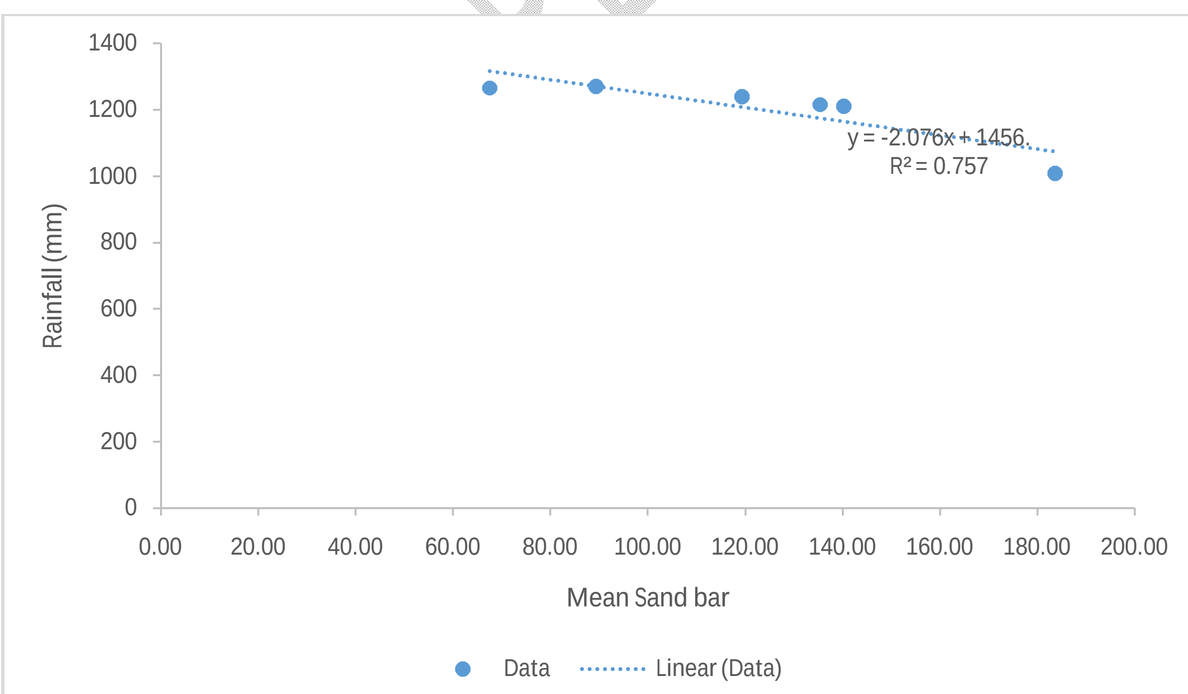

Figure 8: Correlation coefficient between rainfall and Sand bar.

Sandbar Geometric and Shape-Based Parameter Regression Statistics

The regression statistics in Table 4 highlight significant relationships between sandbar parameters length, width, and area demonstrating how these geometric and shape-based features correlate over time. High R^2 values indicate that these morphological parameters not only share a strong association but also evolve in response to environmental factors consistently and predictably.

Table 4: Regression Statistics of Sandbar Parameters Over Time (1974-2024)

Parameter	**R^2**
Length vs Width	0.9737
Length vs Area	0.9027
Width vs Area	0.8921

From Table 4 and Figure 9a shows that the R^2 value of **0.9737 for the Length vs. Width regression** signifies an almost perfect correlation between these dimensions, suggesting that as the length of sandbars increases, their width also scales proportionately. This strong correlation might indicate underlying geological or hydrodynamic controls that dictate the proportional expansion of these two parameters.

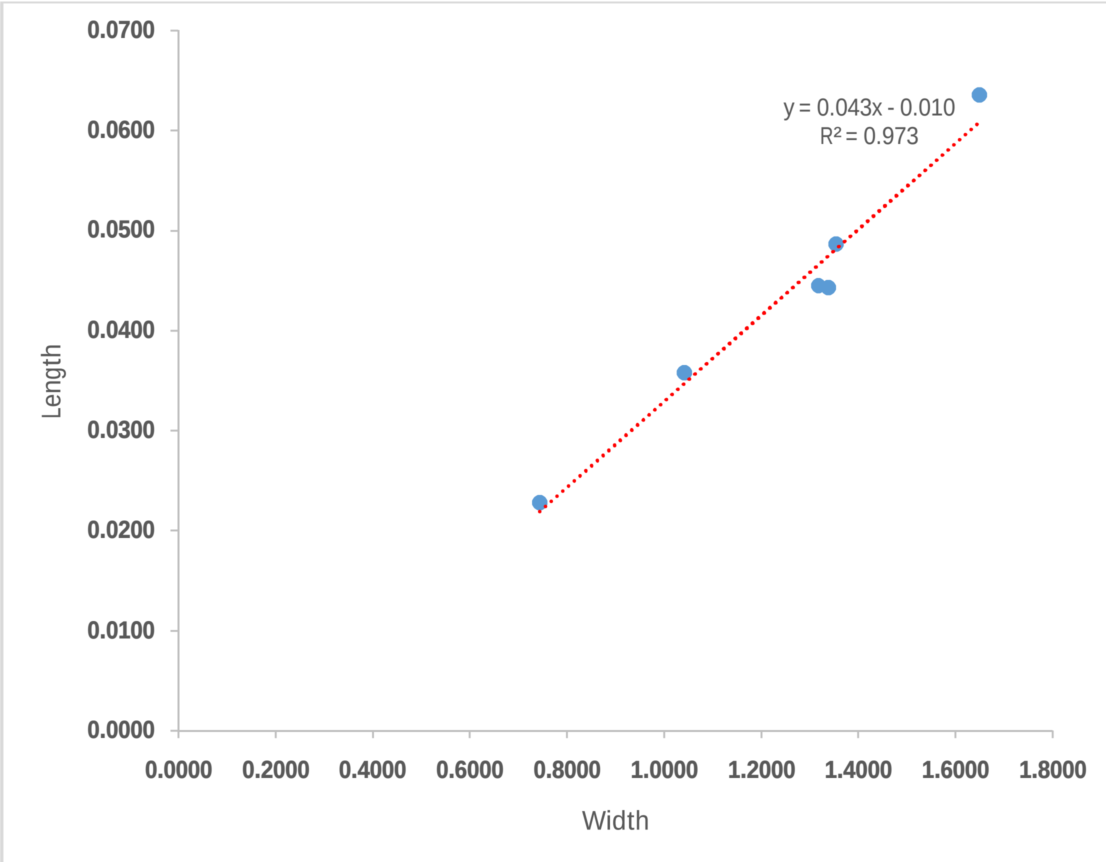

Figure 9a: Linear regression between the length and width of all identified sandbars

In the case of **Length vs. Area in Figure 9b**, the R^2 value of **0.9027** also points to a robust relationship. Although slightly lower than the Length vs. Width correlation, this high value implies that length is a substantial predictor of the sandbar's area. This finding suggests that changes in the length of sandbars, likely due to sediment deposition or erosion, have a significant impact on the overall area, which may be influenced by sediment availability, water levels, and flow dynamics in the river system.

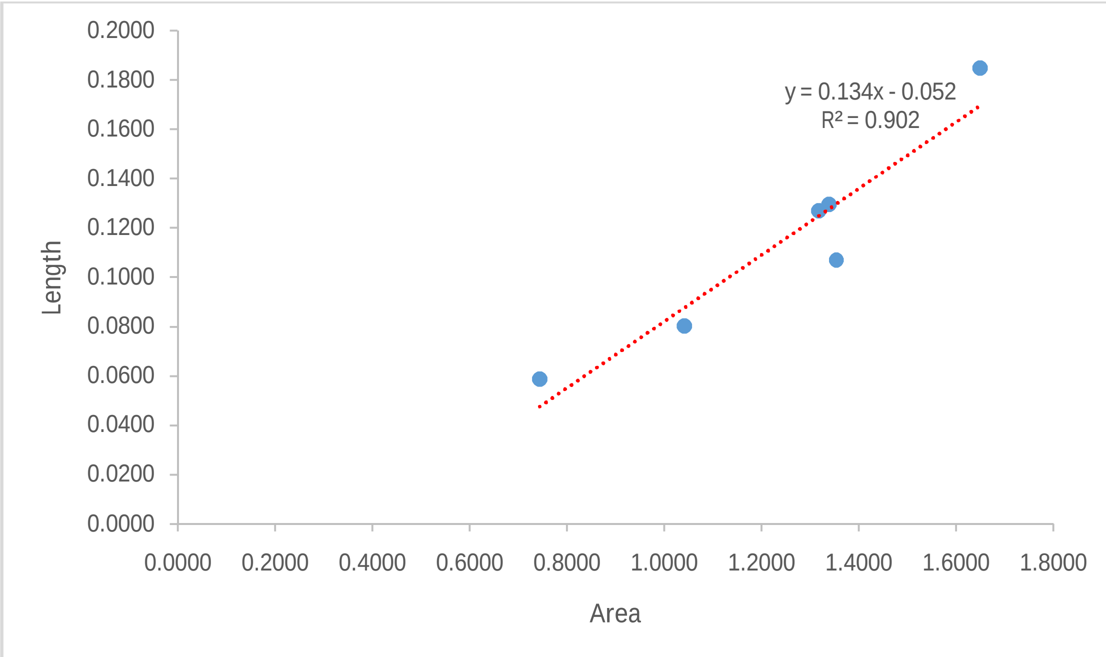

Figure 9b: Linear regression between the length and area of all identified sandbars

Lastly, the **Width vs. Area regression in Table 4 and Figure 9c**, with an R^2 of **0.8921**, suggests a strong but slightly weaker correlation than the other two relationships. This might indicate that width changes have a considerable but somewhat variable effect on the sandbar area, possibly due to differences in local deposition patterns, sediment transport processes, or channel morphology. The slightly lower R^2 could reflect natural variations in how width expansion impacts area compared to length.

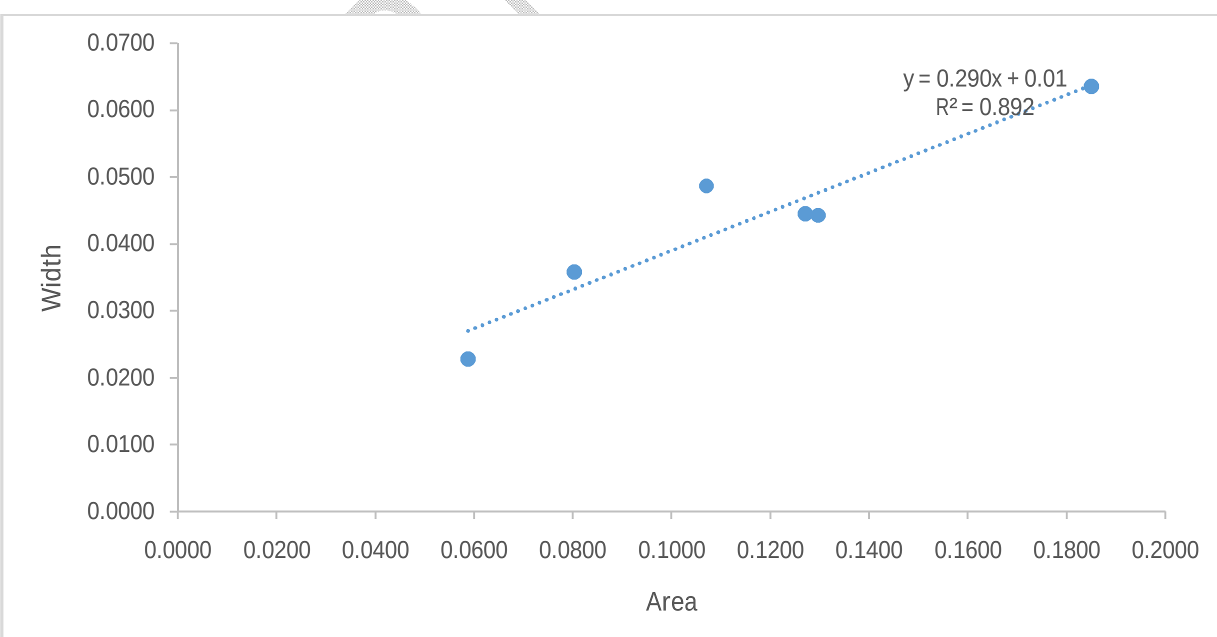

Figure 9c: Linear regression between the width and area of all identified sandbars

The high R^2 values across all three parameters underscore the interconnectedness of sandbar morphometrics, as their shapes and sizes are likely shaped by consistent environmental and hydrodynamic forces [54-55]. These statistical relationships can serve as predictive tools for assessing future sandbar evolution under changing environmental conditions, such as increased flow events or human modifications to river systems.

The influence of grain size on sandbar formation and movement

Sandbars, those ever-shifting ribbons of sand adorning rivers and coastlines, play a crucial role in shaping aquatic ecosystems. Their formation and movement are a delicate dance orchestrated by various factors, with grain size acting as a lead performer. This essay delves into the influence of grain size on sandbar dynamics, exploring how it affects their creation, stability, and vulnerability to climate change. Sandbar formation hinges on the interplay of currents and sediment. Faster currents carry coarser grains (think pebbles and gravel), while finer particles like sand settle out where currents weaken [56].

Table 5: Statistical parameter analysis of Grain size of sediment in sand bar location in River Niger using Folk & Ward [57]

Code	Mean	Interpretation	Sorting	Interpretation	Skewness	Interpretation	Kurtosis
S1	1.23	Medium Sand	0.89	Moderately Sorted	0.25	Fine Skewed	1.08
S2	1.18	Medium Sand	0.84	Moderately Sorted	0.22	Fine Skewed	1.04
S3	2.34	Fine Sand	0.50	Well Sorted	-0.21	Coarse Skewed	1.04
S4	0.43	Coarse sand	0.93	Moderately Sorted	-0.52	Coarse Skewed	1.43
S5	0.60	Coarse sand	0.85	Moderately Sorted	-0.60	Coarse Skewed	1.54
S6	1.00	Coarse sand	0.49	Well Sorted	0.14	Fine Skewed	1.17

The data from Table 5 provides a glimpse into this process. Samples S1 and S2, with a mean grain size of 1.23 and 1.18 respectively, are classified as medium sand based on the Folk & Ward [57] classification system. These moderately sorted samples (sorting values of 0.89 and 0.84) likely represent the core building blocks of a sandbar, accumulating where currents moderate.

Samples S3 and S4 showcase the influence of grain size on specific sandbar features. Sample S3, with a finer grain size (mean = 2.34) and well-sorted nature (sorting = 0.50), might represent the upper, frequently submerged portion of the sandbar. Conversely, samples S4 and S5, with coarser grains (mean = 0.43 and 0.60) and moderate sorting (sorting values of 0.93 and 0.85), are likely indicative of the submerged flanks of the sandbar, exposed to stronger currents that winnow out finer particles.

The size and sorting of sand grains also influence the stability of a sandbar. Well-sorted sandbars, like sample S3 in Table 5, tend to be more stable as the uniform grain size minimizes pore spaces, reducing the erosive effects of water flow[58-59]. Conversely, poorly sorted sandbars with a mix of grain sizes are more susceptible to erosion, particularly during high flows.

The skewness and kurtosis values in Table 5 offer additional result. Samples with positive skewness (like S4 and S5) indicate a dominance of coarser grains, potentially leading to a more loosely packed structure vulnerable to erosion. Kurtosis, on the other hand, reflects the distribution of grain sizes. A platykurtic distribution (low kurtosis value like those in the Table 5) indicates a narrower range of grain sizes, which again contributes to a more stable sandbar structure.Climate change throws a wrench into the delicate balance of sandbar dynamics. Rising sea levels and more frequent extreme weather events like floods can significantly alter the currents and sediment transport patterns in rivers and coastal areas [60]. This can lead to increased erosion of existing sandbars, particularly those composed of finer, less stable sediments.

Comparison with Previous Studies and Global Trends

Comparing our findings with previous studies and global trends in river geomorphology provides context for understanding the observed changes in the River Niger. Studies have shown that sandbar dynamics are influenced by factors such as river flow regulation, climate change, and anthropogenic activities [61].In the context of global trends, the River Niger exhibits similar patterns of sandbar formation and erosion as seen in other major rivers. For instance, the Ganges-Brahmaputra and Mekong rivers also experience significant sandbar dynamics due to seasonal monsoon rains and sediment load variations [62]. Therefore, the study highlights the importance of continuous monitoring using advanced GIS and machine learning techniques to understand and manage river systems effectively. These tools provide valuable outcome into the spatial and temporal patterns of sandbar dynamics, contributing to better river management and conservation strategies.

Ecological and Hydrological Implications of Sandbar Dynamics

The observed reductions in sandbar dimensions have substantial ecological implications, as sandbars serve as habitats for aquatic organisms and influence riverine flow. The declining sandbar area suggests a reduction in habitat availability, which could threaten biodiversity, especially for species reliant on sandbar ecosystems for spawning and foraging [63-65]. As sandbars shrink, the associated habitats diminish, potentially leading to ecosystem imbalances and species decline. The compactness reduction also poses hydrological risks. Less compact sandbars are more susceptible to erosion, increasing sediment transport into the river system and potentially clogging channels. This process can disrupt local water flow, leading to issues such as siltation and increased flood risk.

Broader Implications for River Management and Policy

The observed trends emphasize the need for sustainable river management policies in the Niger Delta. The role of sandbars in influencing sediment flow and stabilizing river channels means that their decline could lead to broader issues, including increased erosion, reduced water quality, and navigational challenges. Sustainable management practices, such as controlled sediment extraction, restoration of natural flow regimes, and implementation of riverbank protection measures, could help mitigate these effects. Similar recommendations were made by Chenet al. [66], who advocated for balancing human activity with ecological preservation in major river systems experiencing similar challenges.

CONCLUSION

The analysis of satellite images, statistical data, and temporal trends in the sandbar morphology of the River Niger from 1974 to 2024 reveals significant geomorphic changes influenced by both natural and anthropogenic factors. The satellite images from 1984 to 2024 illustrate the dynamic nature of the river's sandbars, showcasing their evolution over time. Over these five decades, sandbars have experienced fluctuations in length, area, and perimeter, which collectively show a trend toward decreasing dimensions. For instance, the sandbar length reduced from 1.6502 km in 1974 to a low of 0.7437 km in 2004, indicating a 55% decrease, before rising slightly to 1.3183 km by 2024. Similarly, sandbar area shrank by 68% from 0.185 km² in 1974 to 0.0587 km² in 2004, then modestly recovered to 0.1271 km² by 2024, reflecting potential sediment deposition or hydrological adjustments. This underscores that sandbar morphology is highly dynamic and responsive to both natural and anthropogenic influences. Shape-based parameters, such as Aspect Ratio (AR) and Elongation Ratio (ER), remained relatively stable, suggesting consistent sandbar elongation despite size changes. For example, AR values fluctuated between 24.0168 and 25.9256 over the period, while ER remained steady between 4.8318 and 5.0343, indicating resilience in sandbar shape amidst environmental pressures. However, other shape indices like Circularity and Compactness exhibited reductions, reflecting simpler, elongated sandbar forms more prone to erosion. The study further identified correlations between river area and sandbar dynamics. Notably, when the river area dropped from 46376.54 km² in 1974 to 42711.05 km² in 1984, there was a corresponding reduction in sandbar size. This correlation suggests that river volume and flow rates impact sandbar formation and erosion processes. Regression analysis among sandbar dimensions yielded high R^2 values, such as 0.9737 between length and width, indicating strong relationships between these parameters, likely controlled by sediment transport dynamics.

The implications for river management are profound. Sandbar reductions mean decreased habitat availability, affecting biodiversity and increasing flood risk due to sediment instability. The study advocates for sustainable practices, including sediment regulation and ecological conservation, to balance human needs with river health. These insights align with findings from global river studies, highlighting the Niger River's susceptibility to climate impacts and human activities, underscoring the need for comprehensive monitoring and management policies to protect the river's ecological functions.

Limitations of the Research:

1. The satellite images used may not capture fine-scale morphological changes in the sandbars, limiting the precision of the spatial analysis.
2. While human activities are mentioned as influential, specific anthropogenic factors like dam constructions or sand mining were not directly quantified.
3. While spatial autocorrelation analysis was conducted, the limited geographic scope might not capture wider regional interactions affecting sandbar dynamics.

Highlight Findings:

1. The sandbars experienced significant size reductions from 1974 to 2004, followed by a slight recovery, highlighting their dynamic response to environmental factors.
2. Shape-based parameters such as Aspect Ratio (AR) and Elongation Ratio (ER) remained relatively stable, suggesting a consistent elongation pattern in sandbar formation.

3. Fluctuations in river area aligned with sandbar size changes, showing a potential link between river dynamics and sandbar morphology.
4. Rainfall patterns strongly correlated with sandbar characteristics, underscoring climate's role in influencing sandbar formation and erosion.
5. Regression analysis showed high correlations between sandbar length, width, and area, enabling predictions of future sandbar changes under environmental pressures.

Data Availability Statement

1. The dataset used for the study area analysis was obtained from the United States Geological Survey (USGS) through their Earth Explorer platform (https://earthexplorer.usgs.gov/). The primary source of imagery was the Landsat series of satellites, Sentinel 2, providing a consistent and reliable source of remote sensing data spanning several decades. This imagery captures the evolution of the study area over time with data points from the years 1974, 1984, 1994, 2004, 2014, and 2024 including Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) February 2000.
2. Rainfall data from 1983 to 2023 were sourced from the Center for Hydrometeorology and Remote Sensing (CHRS) (http://www.chrs.web.uci.edu/), incorporating extensive research contributions

References

[1]. Mabogunje, A.L. (2024). Niger River. Encyclopedia Britannica. https://www.britannica.com/place/Niger-River
[2]. Okpara, Donatus & Offiong, Michael Bassey. (2020). Morphodynamics of river and coastal transport of sediments in mega delta basin, Niger Delta Nigeria. IOP Conference Series: Earth and Environmental Science. 424. 012010. 10.1088/1755-1315/424/1/012010.
[3]. Janušaitė R, Jukna L, Jarmalavičius D, Pupienis D, Žilinskas G. (2021). A Novel GIS-Based Approach for Automated Detection of Nearshore Sandbar Morphological Characteristics in Optical Satellite Imagery. *Remote Sensing*. 2021; 13(11):2233.

[4]. Twumasi, Yaw & Merem, Edmund. (2006). GIS and Remote Sensing Applications in the Assessment of Change within a Coastal Environment in the Niger Delta Region of Nigeria. International journal of environmental research and public health. 3. 98-106. 10.3390/ijerph2006030011.

[5]. Afolabi M, Darby S. (2022) Spatial and Temporal Variations in Shoreline Changes of the Niger Delta during 1986–2019. *Coasts*. 2022; 2(3):203-220.

[6]. Goldstein, Evan & Coco, Giovanni & Plant, Nathaniel. (2019). A review of machine learning applications to coastal sediment transport and morphodynamics. Earth-Science Reviews; vol; 194 ; 11 p. 97- 108 ; 10.31223/osf.io/cgzvs.

[7]. Han, Q., Zeng, Y., Zhang, L., Cira, C.-I., Prikaziuk, E., Duan, T., Wang, C., Szabó, B., Manfreda, S., Zhuang, R., and Su, B.: Ensemble of optimised machine learning algorithms for predicting surface soil moisture content at a global scale, Geosci. Model Dev., 16, 5825–5845, https://doi.org/10.5194/gmd-16-5825-2023, 2023.

[8]. Janušaitė, Rasa &Karaliunas, Viktoras&Bevainis, Linas. (2019). Application of Remote Sensing Methods in Research of Nearshore Sandbars, Curonian Spit, Lithuania. Baltic Journal of Modern Computing. 7. 10.22364/bjmc.2019.7.4.08.

[9]. Gijsman, Rik &Ruessink, Gerben & Visscher, Jan &Schlurmann, Torsten. (2020). Observations on decadal sandbar behaviour along a large-scale curved shoreline. Earth Surface Processes and Landforms. 10.1002/esp.5041.

[10]. Eteh, D.R., Paaru, M., Egobueze, F.E. *et al.* Utilizing Machine Learning and DSAS to Analyze Historical Trends and Forecast Future Shoreline Changes Along the River Niger, Niger Delta. *Water Conserv Sci Eng* **9**, 91 (2024). https://doi.org/10.1007/s41101-024-00324-1

[11]. Alevizos E, Nicodemou VC, Makris A, Oikonomidis I, Roussos A, Alexakis DD. Integration of Photogrammetric and Spectral Techniques for Advanced Drone-Based Bathymetry Retrieval Using a Deep Learning Approach. *Remote Sensing*. 2022; 14(17):4160.

[12]. Etu-Efeotor JO, Akpokodje EG (1990). Aquifer systems of the Niger Delta. J. Min. Geol. 26(2):279-285.

[13]. Short KC, Stauble AJ (1967). Outline geology of the Niger Delta. Bull. Am. Assoc. Pet. Geol. 54:761-779.

[14]. Weber, K. J. and Daukoru, E. M., 1975. Petroleum Geology of the Niger Delta: Proceedings of the ninth World Petroleum Congress, volume 2, Geology: London, Applied Science Publishers, Ltd

[15]. Etu-Efeotor JO, Odigi MI (1983). Water supply problems in the Eastern Niger Delta. J. Min. Geol. 20(1&2):183-193.

[16]. Udom, G.J and Amah, E.A (2006). Quality Status of Groundwater in Yenagoa and its Environs, Bayelsa State, Nigeria. Journal of Scientific and Industrial Studies, 4(1): 45 – 51.

[17]. Nguyen, P., E.J. Shearer, H. Tran, M. Ombadi, N. Hayatbini, T. Palacios, P. Huynh, G. Updegraff, K. Hsu, B. Kuligowski, W.S. Logan, and S. Sorooshian (2019). The CHRS Data Portal, an easily accessible public repository for PERSIANN global satellite precipitation data, Nature Scientific Data, Vol. 6, Article 180296, 2019. doi: https://doi.org/10.1038/sdata.2018.296

[18]. Sorooshian, S., P. Nguyen, S. Sellars, D. Braithwaite, A. AghaKouchak, and K. Hsu, (2014): Satellite-based remote sensing estimation of precipitation for early warning systems,

Extreme Natural Hazards, Disaster Risks and Societal Implications, A. Ismail-Zadeh, J.U. Fucugauchi, A. Kijko, K. Takeuchi, and I. Zaliapin, Cambridge University Press, 99-111.
[19]. Sorooshian, S., X. Gao, K. Hsu, R.A. Maddox, Y. Hong, B. Imam, and H.V. Gupta, (2002) Diurnal Variability of Tropical Rainfall Retrieved from Combined GOES and TRMM Satellite Information, Journal of Climate, Vol.15, 983-1001, 2002.
[20]. Hsu, K., H.V. Gupta, X. Gao, and S. Sorooshian, Rainfall Estimation from Satellite Imagery, Chapter 11 of Artificial Neural Networks in Hydrology, Edited by R.S. Govindaraju and A.R. Rao, Published by Kluwer Academic Publishers, P.O. Box 17, 3300 AA Dordrecht, The Netherlands, pp 209-234, 2000.
[21]. Hsu, K., H.V. Gupta, X. Gao, S. Sorooshian, and B. Imam, SOLO-An Artificial Neural Network Suitable for Hydrologic Modeling and Analysis, Water Resources Research, Vol.38, No.12. 1302, 2002.
[22]. Hsu, K., H.V. Gupta, X. Gao, and S. Sorooshian, Estimation of Physical Variables from Multiple Channel Remotely Sensed Imagery Using a Neural Network: Application to Rainfall Estimation, Water Resources Research, 35(5), 1605-1618, 1999.
[23]. Hsu, K., X. Gao, S. Sorooshian, and H.V. Gupta, Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks, Journal of Applied Meteorology, Vol. 36, No. 9, 1176-1190, 1997.
[24]. Blaschke, T. (2010) Object Based Image Analysis for Remote Sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65, 2-16.
[25]. Baatz, M. &Schape, A. (2000) Multiresolution Segmentation: An Optimization Approach for High Quality Multi-Scale Image Segmentation. In: Strobl, J., Blaschke, T. and Griesbner, G., Eds., AngewandteGeographischeInformations-Verarbeitung, XII, Wichmann Verlag, Karlsruhe, Germany, 12-23.
[26]. McFeeters, S.K. (1996) The Use of the Normalized Difference Water Index (NDWI) in the Delineation of Open Water Features. International Journal of Remote Sensing, 17, 1425-1432.
[27]. Jensen, J.R. (2005) Introductory Digital Image Processing: A Remote Sensing Perspective. 3rd Edition, Pearson Prentice Hall, Upper Saddle River, NJ.
[28]. Cortes, C., Vapnik, V.(1950) Support-vector networks. Mach Learn 20, 273–297 (1995).
[29]. Moran, P. A. P. "Notes on Continuous Stochastic Phenomena". Biometrika. 37 (1): 17–23.
[30]. Pearson, K. (1895) Notes on Regression and Inheritance in the Case of Two Parents Proceedings of the Royal Society of London, 58, 240-242.
[31]. Massazza G, Bacci M, Descroix L, Ibrahim MH, Fiorillo E, Katiellou GL, Panthou G, Pezzoli A, Rosso M, Sauzedde E, et al. Recent Changes in Hydroclimatic Patterns over Medium Niger River Basins at the Origin of the 2020 Flood in Niamey (Niger). *Water*. 2021; 13(12):1659. https://doi.org/10.3390/w1312165
[32]. Wang, P., Fu, K., Huang, J., Duan, X., & Yang, Z. (2020). Morphological changes in the lower Lancang River due to extensive human activities. *PeerJ*, *8*, e9471. https://doi.org/10.7717/peerj.9471
[33]. Gu, Z., Fan, H., & Wang, Y. (2020). Dynamic characteristics of sandbar evolution in the lower Lancang-Mekong River between 1993 and 2012 in the context of hydropower

development. *Estuarine, Coastal and Shelf Science, 237*, 106678. https://doi.org/10.1016/j.ecss.2020.106678
[34]. Petts, G. E. (1984). Sedimentation within a regulated river. *Earth Surface Processes and Landforms, 9*(2), 125-134.
[35]. Hickin, E. J., & Nanson, G. C. (1984). Lateral migration rates of river bends. *Journal of hydraulic engineering*, *110*(11), 1557-1567.

[36]. Naciri, W., Boom, A., Payne, M., Browne, N., Evans, N. J., Holdship, P., Rankenburg, K., Nagarajan, R., McDonald, B. J., McIlwain, J., and Zinke, J.: Massive corals record deforestation in Malaysian Borneo through sediments in river discharge, Biogeosciences, 20, 1587–1604, https://doi.org/10.5194/bg-20-1587-2023, 2023.
[37]. Lawson SK, Udo K, Tanaka H, Bamunawala J. Littoral Drift Impoundment at a Sandbar Breakwater: Two Case Studies along the Bight of Benin Coast (Gulf of Guinea, West Africa). *Journal of Marine Science and Engineering*. 2023; 11(9):1651. https://doi.org/10.3390/jmse11091651
[38]. Wright, S., & Kaplinski, M. (2011). Flow structures and sandbar dynamics in a canyon river during a controlled flood, Colorado River, Arizona. *Journal of Geophysical Research F: Earth Surface, 116*(F1). https://doi.org/10.1029/2009JF001442
[39]. Taveneau A, Almar R, Bergsma EWJ, Cissé COT, Sy BA, Ndour A. Monitoring Temporal Sandbar and Shoreline Changes at Saint Louis, Senegal: Using Sentinel-2 Imagery (2015–2022). *Remote Sensing*. 2024; 16(19):3551. https://doi.org/10.3390/rs16193551
[40]. Kuang C, Han X, Zhang J, Zou Q, Dong B. Morphodynamic Evolution of a Nourished Beach with Artificial Sandbars: Field Observations and Numerical Modeling. *Journal of Marine Science and Engineering*. 2021; 9(3):245. https://doi.org/10.3390/jmse9030245
[41]. Paul M. (Mitch) Harris, Samuel J. Purkis, James Ellis; Analyzing Spatial Patterns in Modern Carbonate Sand Bodies From Great Bahama Bank. *Journal of Sedimentary Research*2011;; 81 (3): 185–206. doi: https://doi.org/10.2110/jsr.2011.21
[42]. *Leuven, J., Haas, T., Braat, L., & Kleinhans, M.G. (2018). Topographic forcing of tidal sandbar patterns for irregular estuary planforms. Earth Surface Processes and Landforms, 43, 172 - 186.*
[43]. Rai, P.K., Chandel, R.S., Mishra, V.N. *et al.* Hydrological inferences through morphometric analysis of lower Kosi river basin of India for water resource management based on remote sensing data. *Appl Water Sci* **8**, 15 (2018). https://doi.org/10.1007/s13201-018-0660-7
[44]. Eteh, D., Akpofure, E., &Otobo, S. (2022). GIS & Remote Sensing Based Morphometric Parameters and Topographic Changes of the Lower Orashi River in Niger Delta. *Journal of Atmospheric Science Research*, *5*(1), 1–10. https://doi.org/10.30564/jasr.v5i1.3873
[45]. Li, Yuan & Zhang, Chi & Dai, Weiqi & Chen, Dake & Sui, Titi & Xie, Mingxiao & Chen, Songgui. (2022). Laboratory investigation on morphology response of submerged artificial sandbar and its impact on beach evolution under storm wave condition. Marine Geology. 443. 106668. 10.1016/j.margeo.2021.106668.
[46]. Liu X, Luo X, Lu C, Zhang G, Ding W. The Impact of Foreshore Slope on Cross-Shore Sediment Transport and Sandbar Formation in Beach Berm Nourishment. *Water*. 2024; 16(15):2212. https://doi.org/10.3390/w16152212

[47]. Jana R. Cox, YmkjeHuismans, Jasper Leuven, et al. Anthropogenic effects on the contemporary sediment budget of the lower Rhine-Meuse Delta channel network. *ESS Open Archive* . March 22, 2021
[48]. Janušaitė R, Jukna L, Jarmalavičius D, Pupienis D, Žilinskas G. A Novel GIS-Based Approach for Automated Detection of Nearshore Sandbar Morphological Characteristics in Optical Satellite Imagery. *Remote Sensing*. 2021; 13(11):2233. https://doi.org/10.3390/rs13112233
[49]. Lee, S. H., Hyun, C. U., & Kim, S. B. (2024). Assessing sandbar morphology in the Nakdong River Estuary using SPOT series satellite imagery. *Marine Georesources&Geotechnology*, 1–11. https://doi.org/10.1080/1064119X.2024.2378074
[50]. Sweeney, Mark & Fischer, Ben & Wermers, Karen & Cowman, Tim. (2018). Eolian and fluvial modification of Missouri River sandbars deposited by the 2011 flood, USA. Geomorphology. 327. 10.1016/j.geomorph.2018.10.018.
[51]. Miselis, J.L., Flocks, J.G., Zeigler, S., Passeri, D., Smith, D.R., Bourque, J., Sherwood, C.R., Smith, C.G., Ciarletta, D.J., Smith, K., Hart, K., Kazyak, D., Berlin, A., Prohaska, B., Calleson, T., and Yanchis, K., 2021, Impacts of sediment removal from and placement in coastal barrier island systems: U.S. Geological Survey Open-File Report 2021–1062, 94 p., https://doi.org/10.3133/ofr20211062.
[52]. Ferreira, A. M., Coelho, C., & Silva, P. A. (2024). Numerical evaluation of the impact of sandbars on cross-shore sediment transport and shoreline evolution. *Journal of Environmental Management*, *370*, 122835. https://doi.org/10.1016/j.jenvman.2024.122835
[53]. Gurnell, A. M. (2016). Trees, wood and river morphodynamics: results from 15 years research on the Tagliamento River, Italy. *River Science: Research and Management for the 21st Century*, 132-155.
[54]. Kondolf, G. PROFILE: Hungry Water: Effects of Dams and Gravel Mining on River Channels .*Environmental Management* **21** , 533 –551 (1997). https://doi.org/10.1007/s002679900048
[55]. Leopold, L.B., Wolman, M.G. and Miller, J.P. (1964) Fluvial Processes in Geomorphology. Freeman, San Francisco, 522 p.
[56]. Komar, P. D. (1996). Mechanics of Coarse Sediment Transport. CRC Press.
[57]. Folk, R. L., & Ward, W. C. (1957). Brazos River bar: a study in the significance of grain size parameters. Journal of Sedimentary Research, 27(1), 3-26.
[58]. Sun, X., Liu, Y., & Liu, Z. (2017). Influences of grain size distribution on the erosion and stability of riverbeds. Journal of Mountain Science, 14(3), 446-459.
[59]. Syvitski, J. P. M., Vörösmarty, C. J., Kettner, A. J., & Green, P. (2005). Impact of humans on the flux of terrestrial sediment to the global coastal ocean. Science, 308(5720), 376-380
[60]. Knighton, D. (1998). Fluvial Forms and Processes: A New Perspective. Hodder Education.
[61]. Gupta, H., Kao, S. J., & Dai, M. (2012). The role of mega dams in reducing sediment fluxes: A case study of large Asian rivers. Journal of Hydrology, 464, 447-458.
[62]. Islam, M & Yamaguchi, Y & Ogawa, K. (2001). Suspended sediment in the Ganges and Brahmaputra Rivers in Bangladesh: Observation from TM and AVHRR data. Hydrological Processes. 15. 493 - 509. 10.1002/hyp.165.
[63]. Marjorie Jane G. Badilla, Sarah Jane T. Pabatang, Diana Rose Norberte, Rissa L. Mercado, Minie L. Bulay, Julie S. Berame (2023), Diversity index of species in sandbar present in estuarine

ecosystem of Agusan River, Philippines: Its threat, management and conservation; IJB, V23, N2, August, P47-59
[64]. Malhi, Y., Franklin, J., Seddon, N., Solan, M., Turner, M. G., Field, C. B., & Knowlton, N. (2020). Climate change and ecosystems: threats, opportunities and solutions. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences*, *375*(1794), 20190104. https://doi.org/10.1098/rstb.2019.0104
[65]. Rafferty, J. P. (2024, October 21). biodiversity loss. Encyclopedia Britannica. https://www.britannica.com/science/biodiversity-loss
[66]. Chen, J., Xue, J., Gu, K., & Wang, Y. (2024). Balancing urban expansion with ecological integrity: An ESP framework for rapidly urbanizing small and medium-sized cities, with insights from Suizhou, China.