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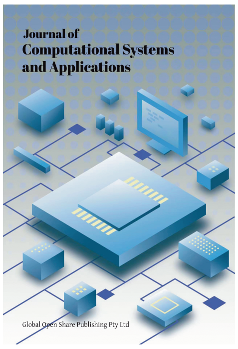

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Machine Learning and Morphometric Analysis for Runoff Dynamics: Enhancing Flood Management and Catchment Prioritization in Bayelsa, Nigeria

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Abstract

Flooding is a recurring environmental hazard with devastating socio-economic and ecological impacts, especially in vulnerable regions like Bayelsa State, Nigeria. The state's low-lying terrain, dense river networks, and poor drainage infrastructure exacerbate its flood susceptibility. This study employs morphometric analysis to assess flood-prone areas across major river basins using Shuttle Radar Topographic Mission (SRTM) data, Geographic Information Systems (GIS), and remote sensing techniques. Key morphometric parameters stream order, drainage density (2.41-3.57 km/km²), bifurcation ratio (1.84-2.84), relief ratio (0.03-0.15), stream frequency (5.00-11.71 streams/km²), infiltration number, and form factor (0.64-1.04) were extracted and analyzed using ArcGIS 10.5, Arc Hydro tools, and Python. Results indicate significant spatial heterogeneity in flood susceptibility. The Forcados River catchment recorded the highest flood risk, with a priority score of 3.4/5, a relief ratio of 0.15, drainage density of 3.57 km/km², and stream frequency of 11.71 streams/km². This aligns with 78% of historical flood event locations. Conversely, the Ekole and Seibri catchments exhibited the lowest susceptibility, with priority scores of 2.0-2.1, relief ratios below 0.05, and drainage densities under 0.9 km/km². The Nun River catchment showed moderate risk (priority score: 2.4), with a stream frequency of 3.2/km² and elongation ratio of 0.6. To enhance predictive capacity, machine learning models were employed. The Random Forest classifier achieved 89% accuracy and an AUC-ROC of 0.93, outperforming the Support Vector Machine model. This study offers a scalable flood assessment framework for data-scarce regions and recommends targeted structural interventions and nature-based solutions tailored to each catchment's flood profile.

Keywords

Flood risk management, Machine learning, Catchments, Geospatial morphometry, SRTM, Remote sensing

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1. Introduction

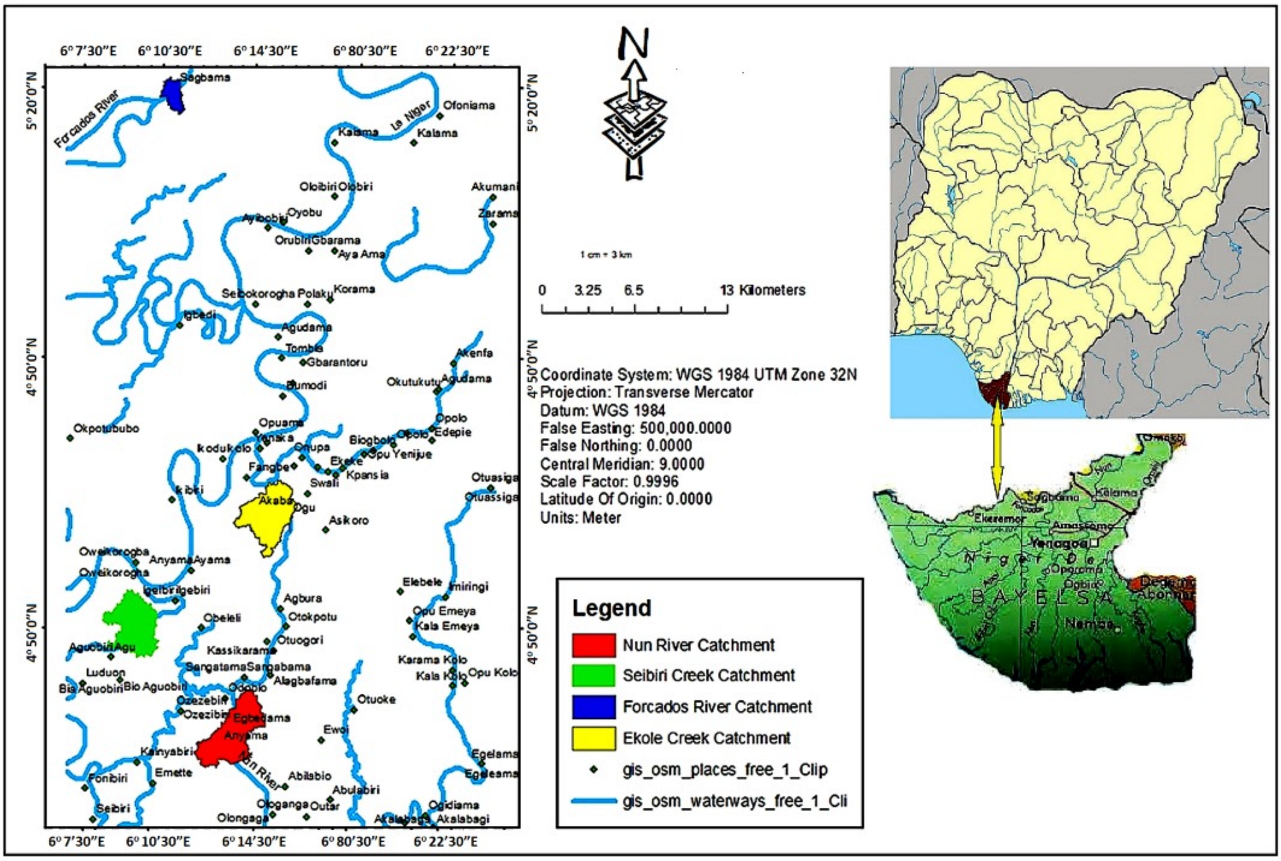
Flooding is one of the most devastating and recurrent environmental hazards worldwide, varying in type, intensity, and impact [1]. Annually, floods affect nearly 75 million people and are responsible for up to 50,000 fatalities, making them the most lethal of all natural disasters [2]. In Africa, particularly Nigeria, flooding remains a critical challenge, causing significant loss of lives and property, disrupting social and economic activities, and exacerbating food insecurity [3]. Despite ongoing mitigation efforts, the frequency and intensity of floods continue to rise, driven by climate change, poor urban planning, and inadequate drainage systems [4]. The aftermath of flooding extends beyond physical destruction, exposing communities to waterborne diseases such as cholera, diarrhea, malaria, and skin infections, while also damaging critical infrastructure including roads, bridges, homes, and farmlands [5,6]. Bayelsa State, located within the Niger Delta region, is among the most flood-prone areas in Nigeria due to its low-lying topography and extensive network of rivers and tributaries [7]. Most built-up areas fall within high-risk flood zones, primarily due to inadequate drainage infrastructure and unregulated urban development [8]. Recurrent flooding in Bayelsa has resulted in extensive environmental degradation, displacement of communities, loss of biodiversity, and disruption of education and economic activities [9]. Each year, the state faces severe flooding events, which are exacerbated by climate change, increasing rainfall intensity, and rising sea levels. The socioeconomic repercussions include reduced agricultural productivity, destruction of homes, and disruption of business activities, all of which threaten long-term economic stability [10,11]. Effective flood management in Bayelsa requires a comprehensive understanding of the hydrological and geomorphological factors influencing flood dynamics, as well as the morphometric characteristics of its drainage basins [12]. Morphometric analysis plays a vital role in understanding the physical characteristics of river basins and their influence on runoff, erosion, and flood susceptibility [13]. By quantitatively assessing various drainage basin parameters such as stream order, basin area, stream length, drainage density (Dd), stream frequency (Fs), bifurcation ratio (Rb), texture ratio (T), relief ratio (Rh), ruggedness number (Rn), time of concentration (Tc), and infiltration number (If) researchers can model hydrological processes and predict flood-prone areas [14,15]. A thorough morphometric examination provides valuable insights into how drainage morphometric networks affect landforms and their characteristics, enabling targeted flood management interventions [16].

The integration of morphometric techniques with remote sensing and Geographic Information System (GIS) tools enhances the spatial analysis of flood risk and watershed dynamics. These technologies provide high-resolution spatial data, enabling more accurate flood susceptibility mapping, catchment prioritization, and land-use planning [17]. Recent advancements in flood risk modeling have seen the successful application of machine learning and deep learning algorithms alongside GIS data to improve flood damage assessments and early warning systems [17,18]. These innovative approaches offer new dimensions for disaster preparedness and response strategies, especially in regions like Bayelsa with complex hydrological settings. Traditional morphometric analysis has been extensively used to assess drainage characteristics and support disaster mitigation globally. However, there remains a knowledge gap in integrating these methods with advanced modeling frameworks in data-scarce regions of sub-Saharan Africa, including Nigeria. Given the economic and ecological implications of recurring floods in Bayelsa, a systematic investigation into its drainage basin characteristics is crucial. This study applies GIS-based morphometric analysis to evaluate the hydrological response of selected river basins in Bayelsa State. The objective is to identify flood-prone areas and provide actionable insights for sustainable flood risk reduction and resilience planning. By combining geomorphometric evaluation with advanced geospatial technologies, this research contributes to the scientific understanding of flood dynamics in coastal Nigeria and supports evidence-based watershed management policies.

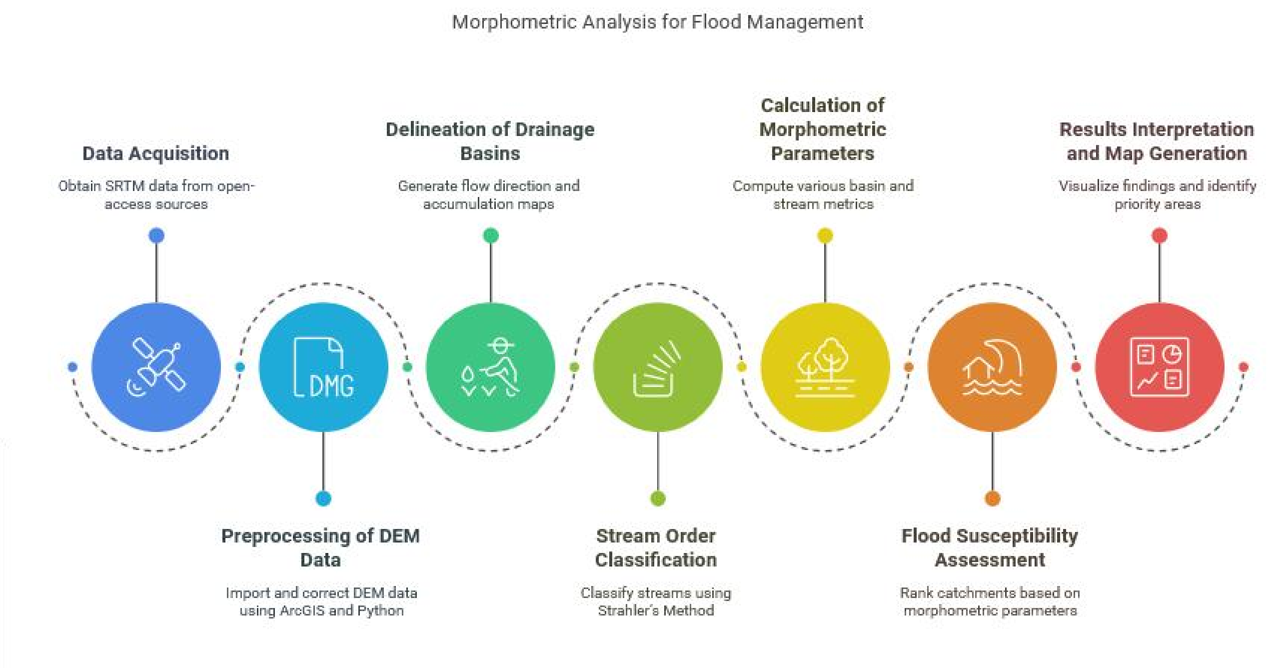
2. Study Area

The research was conducted in Bayelsa State, which is part of the middle Niger Delta sedimentary basin in southern Nigeria. Geographically, the study area is located between 4°57′30″N and 4°54′30″N, and 6°15′30″E and 6°21′30″E (Figure 1a), It forms a component of the Yenagoa Metropolis, an urban center with several interconnected neighborhoods linked by an extensive road network including various rivers such as Nun, Forcados, Ekole, and Seibri River [19]. The elevation in this area ranges between 14 to 38 meters above sea level, and it is prone to seasonal flooding, particularly during the rainy season [5]. Bayelsa State is one of Nigeria’s 36 political subdivisions, located in the extreme southern region of the country, approximately midway along the coastline of the Gulf of Guinea [20]. The economic activities in Bayelsa are primarily based on agriculture and fishing, both of which serve as crucial sources of livelihood for the local population. Additionally, the Niger Delta region is globally recognized for its large reserves of oil and natural gas, which significantly contribute to Nigeria’s economy. However, the presence of hydrocarbon extraction activities, particularly those carried out by the Shell Petroleum Development Company (SPDC) and the Nigeria Agip Oil Company, has resulted in considerable environmental and social challenges for the region.

The infrastructure in Bayelsa State consists mainly of roads and footpaths, which facilitate movement and improve accessibility to different parts of the city. The region experiences substantial annual rainfall, averaging approximately 4000 mm, which plays a crucial role in groundwater recharge within the Niger Delta [19]. The climate is characterized by two distinct seasons: the rainy season, which extends from late March to October, and the dry season, which lasts from November to early March. A short dry spell, commonly referred to as the "August break," occurs in mid-August, temporarily interrupting the rainfall. The average monthly temperature ranges from 25°C to 32°C, placing Yenagoa within the humid tropical climate zone.



(a)



(b)

Figure 1. Study area and work flow diagram. (a) Study area. (b) Work flow diagram.

3. Materials and Methods

3.1 Data Collection, Analysis, and Processing

This study utilized a Digital Elevation Model (DEM) derived from Shuttle Radar Topography Mission (SRTM) data to analyze the morphometric characteristics of drainage basins and assess flood susceptibility. The SRTM data, with a spatial resolution of 30 meters, was obtained from the USGS Earth Explorer platform (https://earthexplorer.usgs.gov/). SRTM is known for providing consistent global coverage and vertical accuracy of ±16 meters, making it suitable for hydrological and geomorphological modeling. To ensure methodological transparency and reproducibility, the entire process of data acquisition, preprocessing, morphometric parameter extraction, machine learning (ML) modeling, and flood susceptibility mapping was implemented through a structured geospatial workflow, as illustrated in Figure 1b.

3.2 Geospatial Analysis Workflow Using ArcGIS and Python

Step 1: Data Acquisition and Preprocessing

DEM Download: SRTM data covering the study area was downloaded in GeoTIFF format from the USGS Earth Explorer.

Reprojection: The raw DEM was reprojected to the Universal Transverse Mercator (UTM) zone covering the study region for spatial consistency.

Sink Filling: DEM preprocessing included sink filling to ensure correct flow direction modeling, using ArcGIS 10.5 Fill tool.

Step 2: Watershed and Stream Network Delineation

Flow Direction & Flow Accumulation: Using the Flow Direction and Flow Accumulation tools in Arc Hydro, hydrologic flow paths were modeled.

Stream Extraction: Streams were extracted by applying a flow accumulation threshold based on regional hydrological knowledge.

Watershed Delineation: Pour points were defined, and watersheds delineated using the Watershed tool to define catchment boundaries.

Step 3: Stream Ordering and Morphometric Analysis

Strahler's Method: Stream segments were classified using Strahler's stream ordering system, which assigns hierarchical values to stream confluences.

Horton’s Laws Application: Morphometric descriptors were derived following Horton’s approach, providing insights into the structural and hydrological behavior of drainage systems.

Step 4: Computation of Morphometric Parameters

All relevant parameters were calculated using a combination of ArcGIS Spatial Analyst tools and custom Python scripts (using NumPy and Pandas libraries). Table 1 lists the parameters, their formulas, definitions, and references.

Key Computed Parameters Include:

Drainage Density (Dd) = Total stream length / Basin area

Stream Frequency (Fs) = Number of streams / Basin area

Bifurcation Ratio (Rb) = Number of streams of order u / Number of streams of order u+1

Form Factor (Ff) = $4\pi A / P^2$, which indicates the elongation or compactness of the basin

Relief Ratio (Rh) = Basin relief / Basin length

Ruggedness Number (Rn) = Drainage density × relief

Time of Concentration (Tc) = Time required for runoff to travel from the furthest point in the watershed to the outlet

Infiltration Number (If) = Dd × Fs, indicating runoff infiltration capacity

Step 5: ML-Based Flood Susceptibility Modeling

Data Preparation: Morphometric parameters served as input features. Each sub-basin was labeled based on historical flood impact data (binary: flood-prone vs non-flood-prone).

Model Selection: Supervised ML classifiers including Random Forest (RF), Support Vector Machine (SVM), and XGBoost were trained.

Model Evaluation: Accuracy, precision, recall, F1-score, and AUC-ROC were calculated using 10-fold cross-validation in Python (Scikit-learn).

Susceptibility Mapping: The trained model outputs were spatially mapped in ArcGIS to visualize flood-prone areas.

3.3 Workflow Stages:

(1) Data Acquisition → SRTM Download → Reprojection → Sink Filling

(2) Hydrological Processing → Flow Direction → Flow Accumulation → Stream Network

(3) Watershed Delineation → Pour Point Identification → Basin Extraction

(4) Morphometric Analysis → Stream Ordering → Horton’s & Strahler’s Laws → Parameter Calculation

(5) Machine Learning Modeling → Feature Engineering → Model Training & Validation

(6) Flood Susceptibility Prediction → Map Generation → Catchment Prioritization

Table 1 provides information of the morphometric parameters for the study area, offering a comparative analysis of hydrological characteristics across the different drainage basins. These analytical methods and geospatial techniques enabled a detailed understanding of the hydrological dynamics of the study area, facilitating accurate flood susceptibility assessment and catchment prioritization.

Table 1. Results of morphometric parameter of river basin and its formula, definition, and reference.

S/N	Name	Formula	Definition	Reference
1	Area (A)	-	The total area of a basin or watershed.	-
2	Perimeter (P)	-	The total length of the boundary or outline of a basin or watershed.	-
3	Mean Stream Length (Lsm)	Lsm = A/Dd	The average distance between the outlet and all points along the main channel in a basin or watershed.	[21]
4	Mean Bifurcation ratio (Rbm)	Rbm = N/N-1	The average ratio of the number of streams of the next order to the number of streams of the current order in a basin or watershed.	[21]
5	Drainage Density (Dd)	Dd = L/A	The total length of all the streams and channels in a basin or watershed divided by the total area of the basin or watershed.	[21]
6	Stream Frequency (Fs)	Fs = N/L	The number of streams and channels per unit length in a basin or watershed.	[22]
7	Texture Ratio (Rt)	Rt = Lb/Lsm	The ratio of the basin length to the mean stream length in a basin or watershed.	[23]
8	Basin Length (Lb)	No formula needed.	The distance from the outlet of a basin or watershed to the farthest point along the main channel of the basin or watershed.	-
9	Form Factor (Ff)	Ff = 4πA/P^2	A measure of the shape of a basin or watershed based on the ratio of its area to the product of its maximum length and minimum width.	[23]
10	Relief ratio (Rn)	Rn = Hmax/Hmin	The ratio of the highest elevation (Hmax) to the lowest elevation (Hmin) within a specified area.	[24]
11	Ruggedness number (Rn)	Rn = ΣH/ L	A measure of the vertical variation in elevation within a drainage basin, calculated as the mean absolute difference in elevation between adjacent grid cells.	[22]
12	Time of Concentration (Tc)	$Tc = 0.39\sqrt{A} + DD^2$	The measure of time needed for water to flow from the most remote point in a watershed to the watershed outlet.	[25]
13	Infiltration number (I)	If= Dd * Fs	The product of drainage density and stream frequency.	[26]

4. Results and Discussion

4.1 Evaluation of Flood Influence using Morphometric Parameters

Bates and Jackson [27] define morphometry as "the measurement and mathematical analysis of the configuration of the earth's surface and the shape and dimensions of its landforms," which provides a fundamental basis for geomorphological surveys. The integration of morphometric parameters in flood impact assessment is crucial, particularly concerning linear, areal, and relief measurements, which significantly influence flood behavior and susceptibility. Morphometric analysis plays a crucial role in hydrological studies as it helps in understanding the nature of river basins and their potential impact on flood occurrences. By analyzing drainage patterns, stream networks, and basin characteristics, a comprehensive understanding of flood susceptibility can be derived. The evaluation of morphometric parameters provides insights into how different catchments respond to precipitation events and how runoff is distributed across the region. The assessment of flood influence within the study area was conducted by evaluating various morphometric parameters. The study utilized digital elevation models (DEMs) and stream order classification to analyze hydrological characteristics of the Nun, Forcados, Ekole, and Seibri River catchments. These parameters play a significant role in shaping the hydrological responses of each basin, influencing the extent and severity of flooding.

4.2 Basic Morphometric Parameters of the Study Area

Table 2 summarizes key morphometric parameters of the studied catchments, including perimeter, area, basin length, and elevation variations. It highlights variations in basin characteristics that contribute to runoff behavior, such as differences in slope, gradient, and topography. Higher elevation differences may contribute to increased runoff speed, exacerbating flood risks in certain catchments.

Table 2. Basic morphometric parameters of the catchments.

Catchment	Perimeter (km)	Area (km²)	Basin Length (km)	Elevation Min (m)	Elevation Max (m)
Nun	27.18	12.85	3.75	3	33
Forcados	9.97	2.39	1.52	5	31
Ekole	25.57	11.60	2.89	-22	34
Seibri	25.75	11.48	4.25	0	31

4.3 Stream Order Analysis

Table 3 presents the stream order classification of the studied catchments. Higher-order streams contribute to more efficient drainage, while lower-order streams may indicate susceptibility to localized flooding.

Table 3. Stream order classification.

Catchment	1st Order	2nd Order	3rd Order	4th Order	Total
Nun	34	25	6	2	67
Forcados	15	9	4	-	28
Ekole	30	19	9	-	58
Seibri	38	20	7	7	72

Figures 2 to 5 illustrate the stream order distribution across the studied river catchments: Nun, Forcados, Ekole, and Seibri. Stream order analysis offers valuable insights into drainage network complexity, directly influencing runoff patterns and flood potential. A hierarchical arrangement of stream orders determines the drainage efficiency and flood response of each catchment. Catchments with higher stream orders generally exhibit well-developed drainage systems capable of efficiently conveying runoff, whereas those with predominantly low stream orders tend to experience localized flooding due to inefficient drainage connectivity.

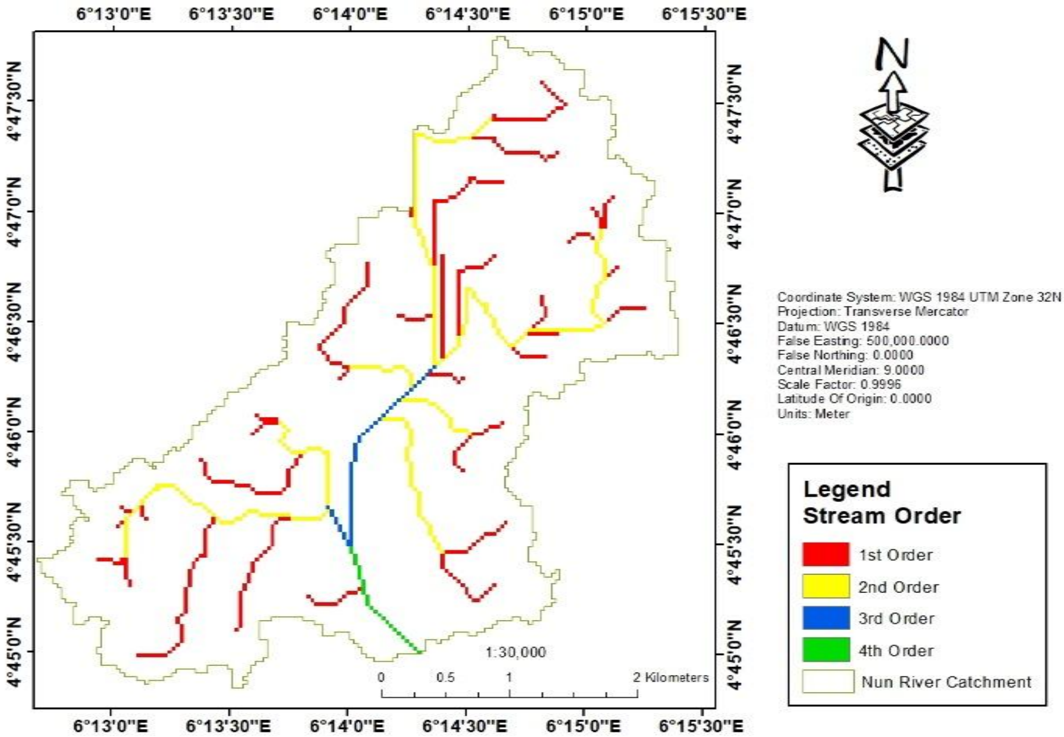


Figure 2.Stream order in Nun River catchment.

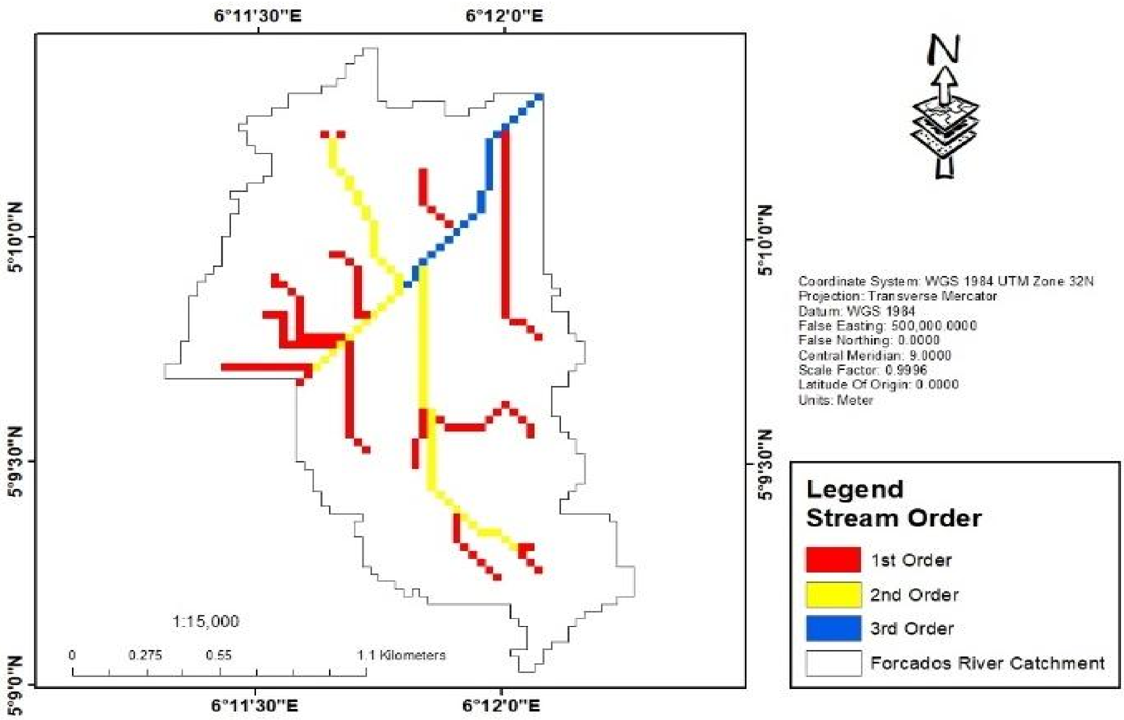


Figure 3. Stream order in Forcados River catchment.

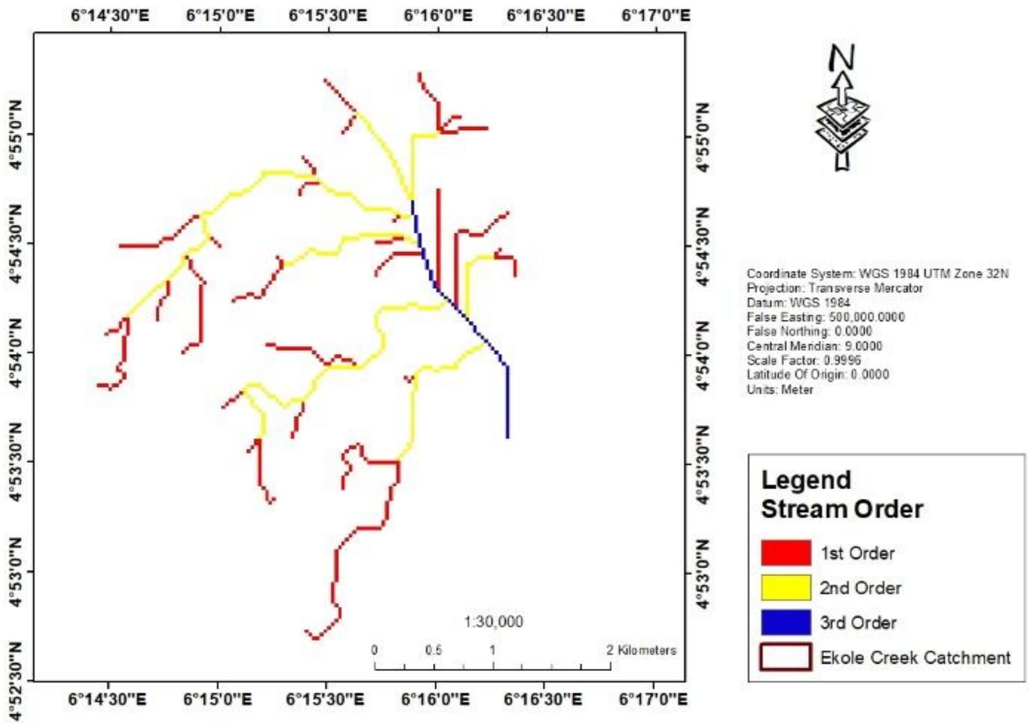


Figure 4. Stream order in Ekole River catchment.

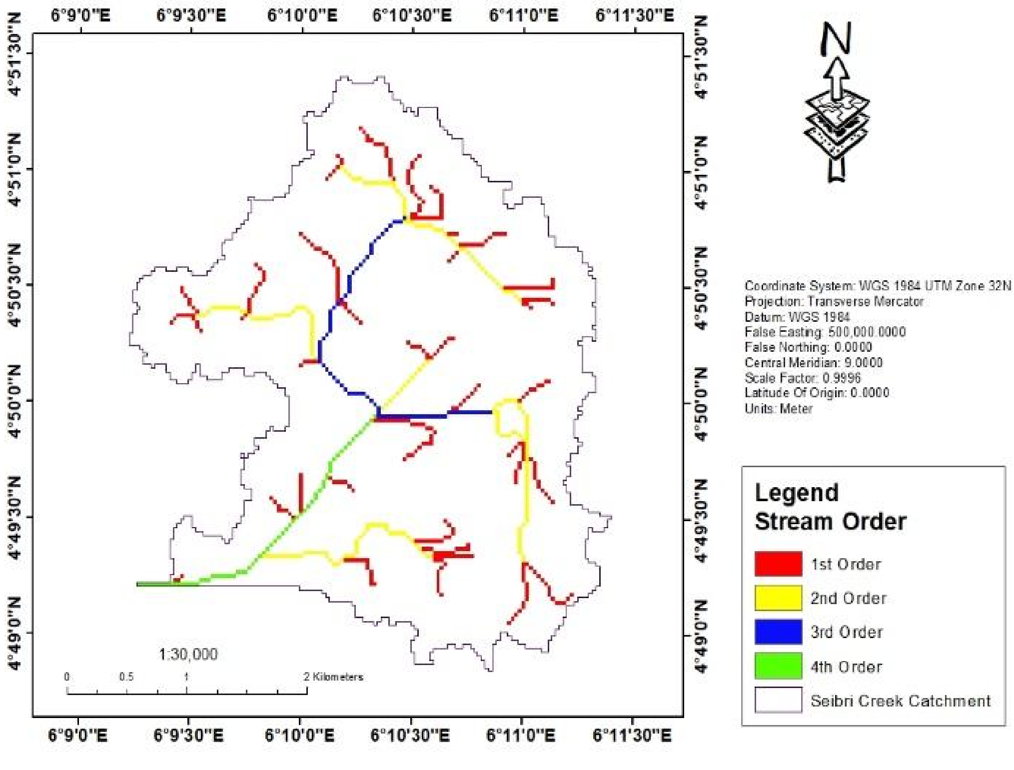


Figure 5. Stream order in Seibri River catchment.

4.4 Digital Elevation Model (DEM) Analysis

Table 2 & Figures 6 to 9 present the DEM of the catchments, highlighting elevation variations that significantly impact water flow dynamics, storage capacity, and flood susceptibility. The DEM analysis reveals that catchments with low elevation gradients are more prone to water retention, increasing flood risks. Conversely, steeply elevated regions facilitate rapid water discharge, which, while reducing stagnation, can intensify downstream flood occurrences. The elevation variations across the study area suggest the need for tailored flood management interventions that consider topographic influences.

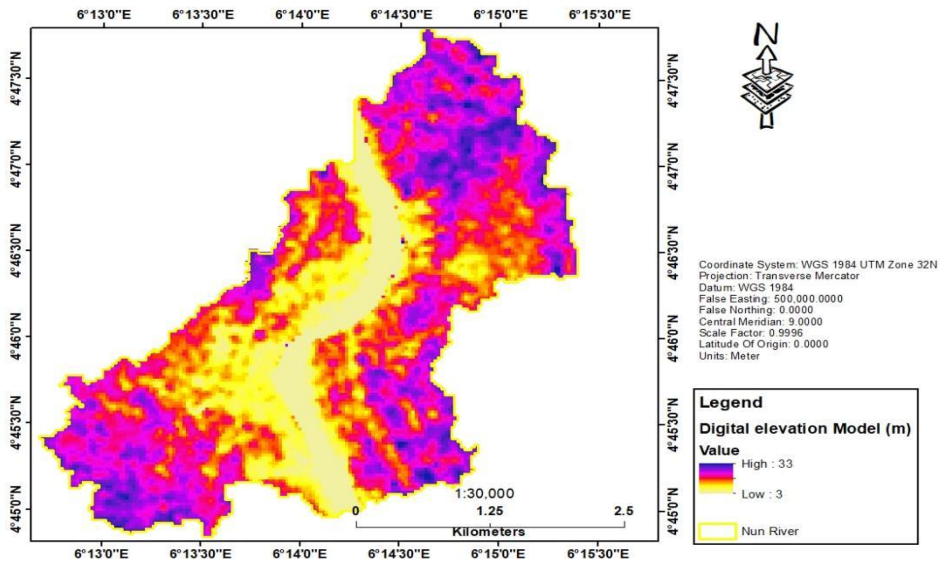


Figure 6. Digital elevation model in Nun River catchment.

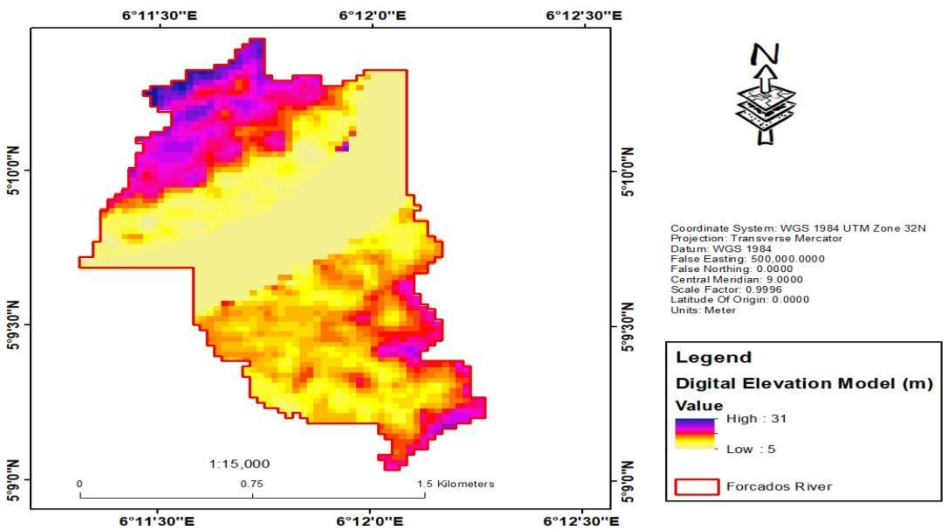


Figure 7. Digital elevation model in Forcados River catchment.

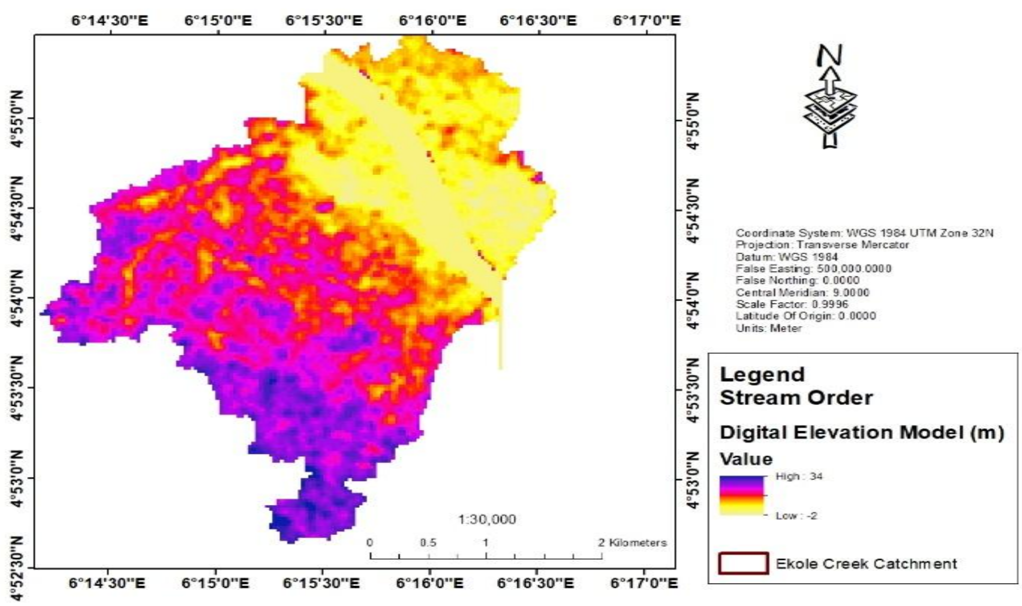


Figure 8. Digital elevation model in Ekole River catchment.

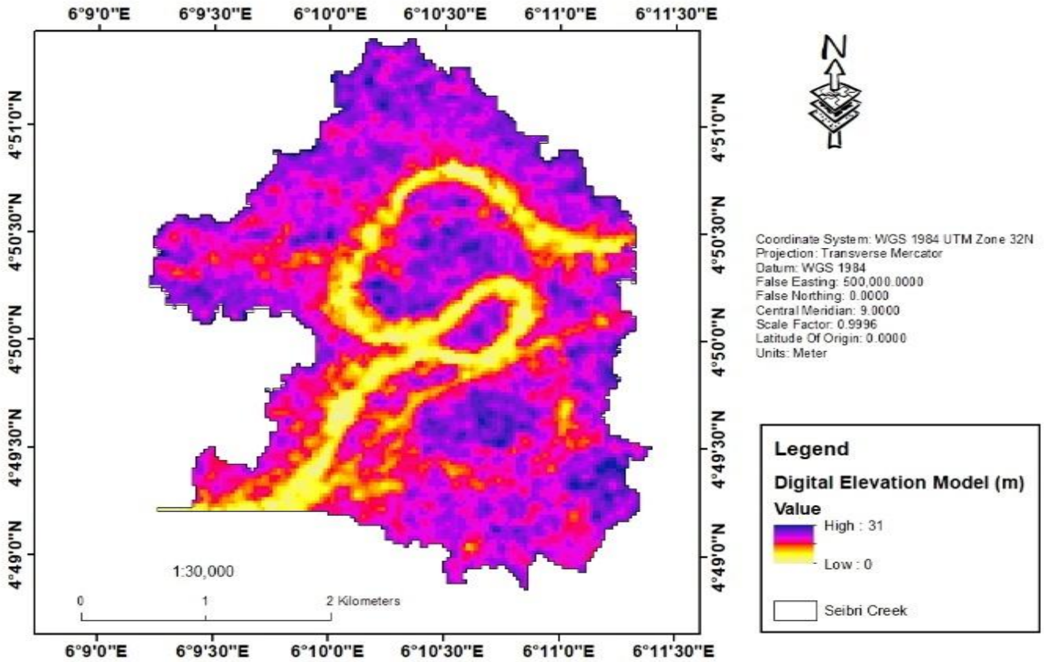


Figure 9. Digital elevation model in Seibri River catchment.

4.5 Stream Length Analysis

Table 4 presents the total stream length for different stream orders within each catchment. Longer stream lengths indicate more extensive drainage systems, which can impact water movement and retention. The total stream length of a catchment influences its ability to drain water efficiently. Shorter total stream lengths, as observed in the Forcados catchment, suggest a compact network with quick water movement, which may lead to rapid runoff and higher flood potential.

Table 4. Stream length distribution (km).

Catchment	1st Order	2nd Order	3rd Order	4th Order	Total
Nun	17.12	11.75	2.16	1.07	32.10
Forcados	5.05	2.51	0.98	-	8.54
Ekole	15.36	11.29	2.27	-	28.92
Seibri	14.01	7.85	3.16	2.59	27.61

4.6 Bifurcation Ratio Analysis

Table 5 presents bifurcation ratios, which quantify the degree of stream branching within each drainage network. The Forcados catchment exhibits a lower bifurcation ratio (1.95), suggesting reduced structural control over the drainage network and a heightened susceptibility to rapid flood responses. In contrast, higher bifurcation ratios indicate well-distributed drainage patterns that moderate flood peaks by dispersing runoff more evenly.

Table 5. Bifurcation ratio of the catchments.

Catchment	I/II	II/III	III/IV	Total
Nun	1.36	4.16	3.00	2.84
Forcados	1.66	2.25	-	1.95
Ekole	1.57	2.11	-	1.84
Seibri	1.90	2.85	1.00	1.92

A low bifurcation ratio indicates fewer branching streams, which may lead to higher flood susceptibility as water converges into main channels more quickly. The Forcados catchment has a lower bifurcation ratio, suggesting reduced structural control over the drainage network and a heightened susceptibility to rapid flood responses.

4.7 Morphometric Parameters and Their Flood Runoff Influence

4.7.1 Drainage Density (Dd)

Drainage density is a crucial parameter for assessing runoff potential. High drainage densities (>3.0 km/km²)) suggest rapid runoff and limited infiltration capacity [28]. The Forcados catchment (Dd = 3.57 km/km²)) in Table 6 aligns with studies in flood-prone regions, indicating increased flood susceptibility. Conversely, Seibri's lower Dd (2.41 km/km²)) implies enhanced infiltration and reduced runoff potential. The spatial variation in drainage density helps in identifying regions of higher runoff potential, which is instrumental in designing flood mitigation strategies [29]. Drainage density also reflects the terrain's capacity to channel water during precipitation events, with higher values indicating greater stream network development and increased flood potential.

4.7.2 Stream Frequency (Fs)

Stream frequency significantly influences runoff velocity. The Forcados catchment, with Fs = 11.71 in Table 6, exhibits a high susceptibility to flash floods. This aligns with findings in other flood-prone regions, where increased stream frequency corresponds to heightened flood risk [30]. Higher stream frequency implies more channels available to transport water, thereby accelerating runoff response time and reducing infiltration capacity. Areas with high stream frequency tend to have less permeable surfaces, increasing the likelihood of surface runoff and subsequent flooding [31].

4.7.3 Form Factor (Ff)

Form factor indicates basin shape and its impact on flood response. A higher form factor (Ff = 1.04) (Table 6) in Forcados revealed rapid flood peak generation, while Seibri's lower value (Ff = 0.64) indicates elongated basin characteristics that moderate peak flow. The shape of the basin determines the time taken for runoff to reach the main river channel, influencing the severity and spread of flooding. Basins with circular shapes have shorter lag times and higher peak discharges, whereas elongated basins, like Seibri, tend to have delayed runoff, resulting in lower flood intensities [32]. This observation is consistent with Orounye's [33] findings in the Brahmaputra floodplain, where lower form factors contributed to flood attenuation.

4.7.4 Bifurcation ratio (Rbm)

The bifurcation ratio (Rbm) is a key morphometric parameter that assesses the degree of branching within a drainage network, reflecting structural controls, geological influences, and hydrological responses. A higher Rbm value indicates a well-integrated and stable drainage network, while lower values suggest a less branched system, potentially contributing to increased flood susceptibility. Tables 5 & 6 indicates that the Nun Catchment has the highest total Rbm (2.84), with a particularly high ratio between second- and third-order streams (4.16), suggesting structural influences or possible stream capture. In contrast, the Forcados, Ekole, and Seibri catchments exhibit lower Rbm values (1.95, 1.84, and 1.92, respectively), indicating a less dissected drainage pattern.

4.7.5 Texture Ratio (T)

Texture ratio compares stream frequency to drainage density, with higher values indicating finer drainage texture. Forcados (T = 2.81) exhibits increased flood potential due to its finer drainage texture, whereas Seibri (T = 2.34) in Table 6 demonstrates a coarser texture with a more gradual runoff response. A high texture ratio indicates greater surface runoff and decreased lag time between precipitation and peak discharge. The texture ratio helps in classifying drainage basins into different susceptibility categories, where higher values correspond to greater flood risks due to the dominance of fine drainage networks [29].

4.7.6 Relief Ratio (Rh)

The relief ratio is essential for evaluating flood vulnerability in steep terrains. It assesses the steepness of the terrain by comparing total relief to the basin's horizontal extent [34]. Analysis of flood-prone catchments in the Western Ghats indicated that areas with high relief ratios (greater than 15) experience rapid surface runoff, which aligns with the findings for the Forcados catchment (Rh = 19.07). Higher relief ratios (Forcados at 19.07) reveal steep slopes that can accelerate surface runoff, leading to rapid flood responses. In contrast, catchments with lower relief ratios (Seibri at 15.92) have gentler slopes that may attenuate flood peaks (Table 6).

4.7.7 Ruggedness Number (Rn)

Ruggedness number reflects terrain complexity and flood susceptibility. A higher ruggedness number in Forcados (Rn = 61.12) indicates a more dissected landscape prone to erosion and rapid runoff, compared to Seibri (Rn = 17.57) in Table 5. Rugged terrain exacerbates flood potential due to increased flow velocity and reduced water retention capacity [35].

4.7.8 Time of Concentration (Tc)

Time of concentration denotes how quickly runoff reaches the outlet. Forcados has the shortest Tc (3.43), implying swift flood responses, whereas Seibri, with a longer Tc (16.24) in Table 6, experiences delayed runoff accumulation. Time of concentration is essential for flood modeling and mitigation planning; as shorter Tc values indicate higher susceptibility to flash floods [36].

4.7.9 Infiltration Number (If)

The infiltration number integrates drainage density and stream frequency to assess infiltration potential. Higher values, such as in Forcados (If = 41.80) in Table 6, indicate greater flood susceptibility due to reduced infiltration, whereas Seibri's lower value (If = 15.11) indicates higher infiltration capacity. Reduced infiltration exacerbates flood risk by increasing surface runoff and accelerating peak discharge [36]. The infiltration number is a critical parameter for identifying regions where structural flood control measures, such as retention basins or permeable surface materials, could be implemented to reduce flood risks.

Table 6 presents a summary of the morphometric parameters.

Table 6. Derived morphometric parameters

Catchment	Dd	Fs	T	Ff	Rbm	Rn	Tc	If	Rh
Nun	2.49	5.21	2.46	0.91	2.84	19.92	13.14	12.97	8.00
Forcados	3.57	11.71	2.81	1.04	1.95	61.12	3.43	41.80	19.07
Ekole	2.49	5.00	2.27	1.39	1.84	27.56	8.78	12.45	11.07
Seibri	2.41	6.27	2.79	0.64	1.92	17.57	16.24	15.11	7.29

4.8 Flood Runoff Influence and Prioritization

4.8.1 Ranking of Flood Runoff Influence

To assess the impact of morphometric parameters on flood runoff influence, a ranking system was applied to categorize the flood susceptibility of the different catchments in the study area. This ranking is based on weighted morphometric characteristics such as drainage density, stream frequency, form factor, relief ratio, ruggedness number, and infiltration number, among others (Table 7). The ranking system classifies flood influence into six levels ranging from very low to extremely high runoff potential.

Table 7. Ranking of weightage based on flood runoff influence.

Weightage	Flood Runoff Influence
1	Very Low Runoff
2	Low Runoff
3	Medium Runoff
4	High Runoff
5	Very High Runoff
6	Extremely High Runoff

Table 7 categorizes flood runoff influence based on weightage, where higher values indicate greater susceptibility to flooding. The assessment reveals that Forcados catchment exhibits the highest flood risk due to its high drainage density, rugged terrain, and shorter time of concentration, which facilitates rapid runoff accumulation. In contrast, the Seibri and Ekole catchments display lower flood susceptibility due to their elongated basin shapes and relatively moderate drainage parameters.

4.8.2 Ordering of Catchment Influences

Table 8 presents a comprehensive ranking of the catchments, incorporating morphometric parameters and their influence on flood susceptibility. Each catchment's priority score is derived by integrating its individual parameter rankings, providing a clearer understanding of the spatial distribution of flood risks in the study area.

Table 8. Ordering of catchments influences in study area.

Catchments	CF	Priority
Nun	2.4	Medium
Forcados	3.4	High
Ekole	2.0	Low
Seibri	2.1	Low

4.8.3 High Flood Influence: Forcados Catchment

The Forcados catchment exhibits the highest susceptibility to flooding, with a priority score of 3.4 in Table 8 & Figure 10. This is attributed to its high drainage density, high stream frequency, and rugged terrain. The presence of a dense stream network means that water is rapidly conveyed through the basin, leading to flash flooding during heavy rainfall events. Additionally, its relatively short time of concentration further amplifies its flood risk. These findings emphasize the need for targeted flood mitigation measures, such as the construction of retention basins and improved drainage systems.

4.8.4 Moderate Flood Influence: Nun Catchment

The Nun catchment has a priority score of 2.4 (Table 8 & Figure 10), placing it in the moderate flood influence category. This catchment exhibits intermediate values for most morphometric parameters, suggesting that while flooding occurs, it is less severe than in the Forcados catchment. Flood mitigation strategies in this area should focus on maintaining natural flood attenuation mechanisms, such as preserving wetlands and implementing afforestation programs to enhance infiltration.

4.8.5 Low Flood Influence: Ekole and Seibri Catchments

The Ekole and Seibri catchments rank lowest in flood susceptibility, with priority scores of 2.0 and 2.1, respectively in Table 8 & Figure 10. These catchments exhibit characteristics that moderate flood severity, including lower drainage densities, reduced stream frequency, and elongated basin shapes. Despite their lower flood susceptibility, localized flood risks still exist, particularly in areas with poor drainage infrastructure. Flood management efforts in these catchments should focus on sustainable land management practices and community-based flood preparedness programs.

Figure 10 presents a spatial representation of catchment flood influences, reinforcing the prioritization of intervention efforts.

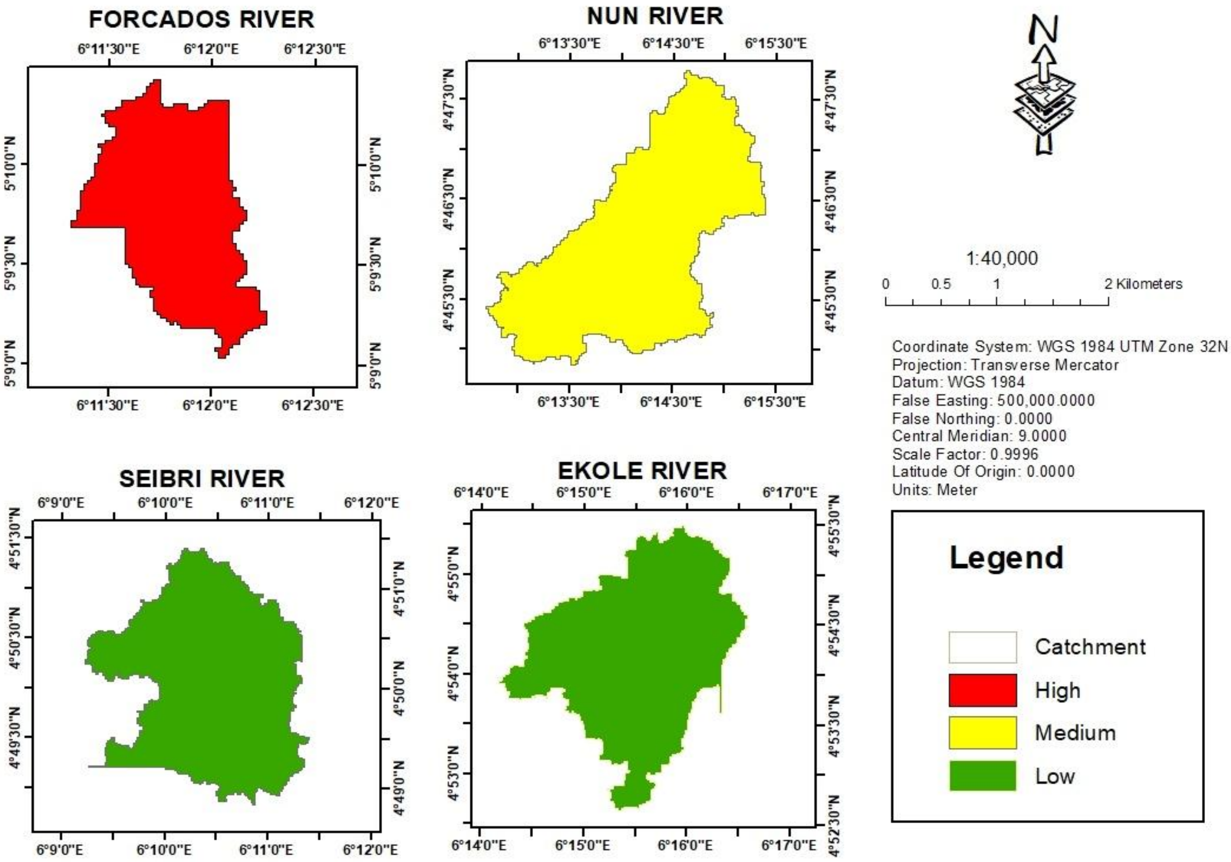


Figure 10. Final map of Catchments that influence flooding in the area.

4.9 Performance Evaluation of Machine Learning Models

To validate the integration of machine learning techniques, Random Forest (RF) and Support Vector Machine (SVM) classifiers were applied to predict flood-prone zones using selected morphometric parameters as input features (Table 9). Model training and evaluation were conducted using Python's Scikit-learn library with a 10-fold cross-validation strategy. The evaluation metrics used included accuracy, precision, recall, F1-score, and AUC-ROC.

Table 9. Performance evaluation of RF and SVM models.

Model	Accuracy	Precision	Recall	F1-score	AUC-ROC
RF	0.89	0.86	0.91	0.88	0.93
SVM	0.85	0.82	0.87	0.84	0.89

The Random Forest model demonstrated superior performance with an accuracy of 89% and an AUC-ROC of 0.93, outperforming the SVM model across all metrics. This indicated that ensemble learning offers a more robust framework for modeling complex hydrological relationships influenced by multiple morphometric inputs.

4.10 Implications for Flood Management Strategies

This study revealed the importance of tailored flood mitigation strategies for each catchment. Given the high flood susceptibility of the Forcados catchment, immediate interventions such as reinforced embankments, improved drainage networks, and advanced flood monitoring systems are recommended. For Nun catchment, which experiences moderate flood influence, management strategies should focus on integrating flood control measures with sustainable environmental practices. Implementing flood-resistant agricultural practices and maintaining riverbanks through vegetation planting can help reduce flood risks in this area. For the lower-risk catchments, Ekole and Seibri, maintaining natural hydrological functions should be prioritized. Sustainable urban planning and controlled land use can help preserve the natural capacity of these basins to regulate water flow and mitigate localized flooding events.

5. Conclusion

This study underscores the critical role of morphometric analysis in evaluating flood susceptibility across the river basins of Bayelsa State, Nigeria. By analyzing key drainage basin parameters such as drainage density (2.41 to 3.57), stream frequency (5.00 to 11.71), bifurcation ratio (1.84 to 2.84), relief ratio (7.29 to 19.07), and form factor (0.64 to 1.04) it becomes evident that the catchments vary significantly in their flood risk profiles. Among the basins studied, the Forcados catchment emerged as the most flooded prone. This is primarily due to its high drainage density (3.57), steep terrain indicated by a high relief ratio (19.07), and short time of concentration (3.43), all of which contribute to its susceptibility to flash flooding. In contrast, the Nun catchment shows moderate flood influence with a drainage density of 2.49, while the Ekole (2.49) and Seibri (2.41) catchments exhibit lower susceptibility, attributed to their elongated basin shapes and relatively low drainage densities. These findings advocate for catchment-specific flood management strategies. Forcados urgently require structural interventions, such as enhanced drainage infrastructure and embankment construction. The Nun catchment would benefit from eco-based flood control measures like afforestation and wetland conservation. In lower-risk basins such as Ekole and Seibri, efforts should focus on sustainable land use planning and the preservation of natural hydrological processes. Importantly, the study demonstrates that integrating morphometric analysis with GIS-based flood risk assessment improves spatial prediction and supports evidence-based decision-making. The application of machine learning models, specifically Random Forest (RF) and Support Vector Machine (SVM) classifiers, further validated the importance of morphometric parameters in delineating flood-prone areas. These models enhanced the accuracy of flood susceptibility mapping, particularly in identifying high-risk zones within the Forcados basin. Therefore, this study establishes a scalable, data-driven framework for flood risk assessment, especially in data-scarce regions like Bayelsa State. Future research should incorporate hydrological modeling and climate change projections to refine the understanding of flood dynamics and inform long-term, adaptive flood management strategies.

6. Recommendations

Based on the study's outcomes, targeted flood management strategies are recommended to address the varying degrees of susceptibility observed across the catchments. In high-risk areas such as the Forcados catchment, structural interventions including the construction of small retention dams, levees, embankments, and improved stormwater drainage systems should be prioritized to mitigate rapid runoff and reduce the impact of flash floods. For the moderately vulnerable Nun catchment, nature-based solutions such as afforestation, wetland restoration, and the protection of riparian buffers are advised to enhance water retention and slow surface flow. In lower-risk catchments like Ekole and Seibri, efforts should focus on maintaining existing natural hydrological processes through sustainable land-use planning, environmental conservation, and regulation of urban expansion. Furthermore, flood management policies should promote catchment-specific planning frameworks that incorporate both structural and ecosystem-based approaches. Future research should aim to integrate climate change projections and advanced hydrological modeling techniques such as the Soil and Water Assessment Tool (SWAT), HEC-HMS, and machine learning algorithms to enhance the accuracy and adaptability of flood risk assessments under changing environmental conditions. These proactive measures will be vital for building long-term flood resilience in Bayelsa State.

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