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Impact of Flood Susceptibility Mapping as an Early Warning Tool in a Changing Environment

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Abstract

In this study, an attempt was made to develop a flood susceptibility map around Ikpoba catchment in Benin City, Nigeria. The communities within the study area include; Agemopa, Odighi, Okohuo, Aihuobabekun, Ogbogiobo, Evboneka, Izakagbo, Ekiadoro, Utekon, Igozula, Ada Obadan, Ogheghe, Uselu, Aho, Igueowieoba, Iguomo, Ugonoba and Oka. Others are; Uweyoba, Urhuokhokhor, Egbiri, Evbuomoma, Ugoneki, Utesi, Utezi and Obaretin community. Ten thematic maps namely; Topographic wetness index (TWI) map, Elevation map, Slope map, Precipitation map, Land use land cover map, Normalized difference vegetation index (NDVI) map, Distance from river map, Distance from road map, Drainage density map and soil map were employed for the study. The thematic maps were thereafter reclassified in order to obtain a uniform scale. To obtain the percentage weight of influence for each of the data, analytical hierarchy process (AHP) was employed to generate a pairwise comparison matrix which validated using the index of consistency. Thereafter weighted overlay method was employed to stack the reclassify maps in order to generate the final flood map. To determine the areas with high flood risk, the flood map was converted to kml file and thereafter projected to google. The outcome revealed that communities such as; Odighi and Okohuo pose a very high risk of flooding while Aihuobabekun, Ogbogiobo, Evboneka, Izakagbo, Ekiadoro, Ogheghe, Uselu and Aho pose a high risk of flooding.

1.0. Introduction

Based on their locations and causes, flooding can generally be divided into four types and they include; River flooding, urban drainage, ground failures and coastal flooding and erosion [1,2,3]. River flooding occurs when the river runoff volume exceeds the channel carrying capacities or due to poor operation of flood control structures upstream. Cities located on low lying areas in the middle or lower reaches of rivers are particularly exposed to serious river flooding [4,5]. Flash floods are common types of riverine flooding that occur when a large amount of water is discharged within a few minutes or hours (three to six hours) of excessive rainfall. Flooding of urban cities which is normally referred to as urban flooding is caused by poor drainage systems and further compounded by the blockade of storm drains with municipal solid wastes and eroded soil sediments [6,7]. Unusually high tides and storm surges caused by severe winds over ocean surfaces are largely responsible for coastal floods in towns or cities located in low lying land near the sea and tidal flats [8,9,10]. Overtopping of dams especially due to inadequate spillways remains the major cause of dam failure which can also lead to flooding.

Factors contributing to flooding can be grouped into meteorological factors, hydrological factors and human induced factors. Meteorological factors contributing to flooding include; Rainfall, Temperature, Snowmelt and cyclonic storms [11, 12,13,14]. Hydrological factors include; surface infiltration level, geometric characteristics of the channel (cross sectional area and shape factor), runoff level, presence of impervious cover and soil moisture condition while human induced factors include; Land use (influence of urbanization and deforestation), global warming and GHG emission resulting to climate change, habitation of flood plains areas, inadequate and poor sizing of drains, poor maintenance culture especially for water carrying structures and land reclamation (especially for coastal and wetland) [15,16]

In general, the impact of flooding is dependent on factors such as location, the height and duration and its nature [16, 17]. Specifically, flood causes damage to human lives, properties, buildings including critical government infrastructures such as; roads, bridges, electricity lines, farm lands including soil erosion and sediment transport and deposition which can consequently results in the pollution of surface water and destruction of aquatic wildlife [18,19]. On account of the danger pose by flood and other water related disaster, researchers all over have clamor for early warning signals that will help for flood preparedness and prevention [20,21,22]. Mapping and analysis of flood susceptibility is one of the most important elements of early warning systems or strategies for prevention and mitigation of future flood situations since it identifies the most vulnerable areas based on physical conditions that determine the propensity for flooding [23, 24]. Therefore, the term susceptibility can also be perceived as one of the dimensions of vulnerability assessment [23,25]. Informing the public about flood risks is an initial step to encourage public participation in flood risk management [24, 26]. Maps are useful tools for informing communities about their flood risk as they can be used for prioritizing local mitigation efforts, such as regulating build-up in flood-prone areas, and identifying which properties should adopt flood-proofing measures (e.g., installing a backwater valve).

Several factors can influence the development of a flood susceptibility map for a specific location. Depending on the physical characteristics of the area to be investigated, flood susceptibility mapping techniques rely on various conditioning factors such as; geology or lithology, morphometric properties (e.g., elevation, slope), river network density, soil types or hydrological soil groups, land use/land cover, and the like.

In selecting the conditioning factors for flood susceptibility analysis, it is important to consider the spatial scale (investigated area) of the analysis [24]. For large spatial scale (national and regional scale analysis), using less factors seems to be rational since it is more difficult to gain the same data (same scale or resolution) for the whole territory. For local scale studies (e.g., catchment scale), a wider range of location-specific data and factors are required, thus allowing for more accurate characterization of the flooding characteristics [25,26]

It is interesting to note that one of the greatest arguments about flood susceptibility mapping is the actual number of conditioning factors to be selected in order to best visualize the physical characteristics that describes the propensity of the study area to flooding [26]. Some researchers have used five factors while others have employed 6, 7, 8 and 10 factors respectively. Although no exact agreement exists on the number of factors, some of the conditioning factors recur in most previous studies and thus can be considered basic factors indicating their important role and

relevance for flood susceptibility mapping. These basic factors include; slope, elevation, land use/land cover, distance from river, drainage density, and lithology.
In this study about 12 conditioning factors which include; geology, slope, elevation, land use/land cover, precipitation, flow length, river distance, road distance, drainage density soil, topographic wetness index (TWI) and normalized vegetation difference index (NDVI) were selected to prepare a flood susceptibility map.

2.0 Methodology

2.1 Description of Study Area

The study area is Ikpoba catchment Benin City, Edo State, Nigeria (Figure 1). Edo State lies roughly between longitude 06^{o} 04'E and 06^{o} 43'E and latitude 05^{o}44' N and 07^{o}34' N (Okoduwa, 1999). Edo State has a tropical climate characterized by two distinct seasons: the wet and dry seasons. The wet season occurs between April and October with a break in August, and an average rainfall ranging from 150 cm in the extreme north of the State to 250 cm in the south. The dry season lasts from November to April with a cold harmattan spell between December and January. The temperature averages about 25 °C (77 °F) in the rainy season and about 28 °C (82 °F) in the dry season. The climate is humid tropical in the southern part and sub-humid in the northern part (Okoduwa, 1999). In order to visualize the spatial scale of the study area and determine the communities within the area, the digital elevation model (DEM) of the study area obtained and converted to kml file, then, it was projected to google in order to determine the communities covered by the study.The outcome is presented in Figures 1.

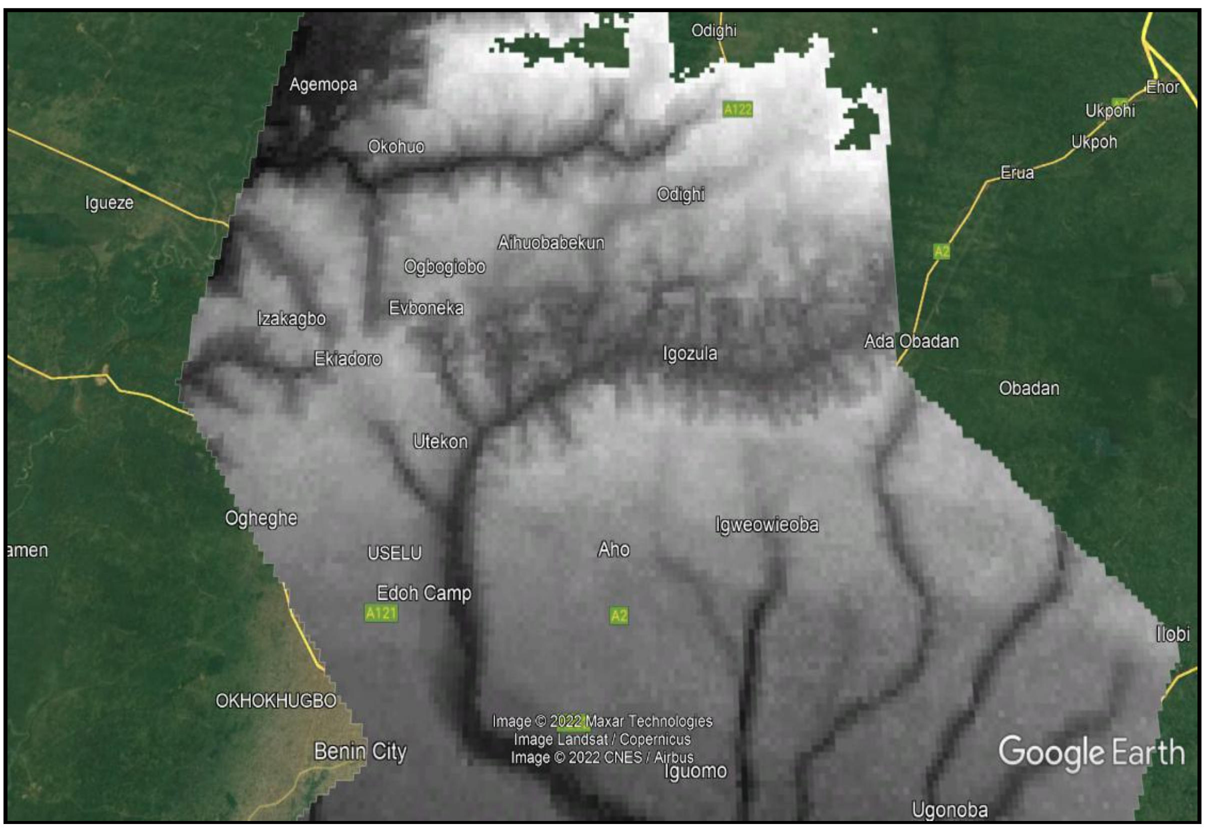


Figure 1: Google earth map of study area

From Figure 1, some of the communities within the study area include; Agemopa, Odighi, Okohuo, Aihuobabekun, Ogbogiobo, Evboneka, Izakagbo, Ekiadoro, Utekon, Igozula, Ada Obadan, Ogheghe, Uselu, Aho, Igueowieoba, Iguomo, Ugonoba and Oka. Others are; Uweyoba, Urhuokhokhor, Egbiri, Evbuomoma, Ugoneki, Utesi, Utezi and Obaretin community.

2.2 Data Requirement

Since floods are multi-dimensional phenomena with spatial and temporal aspects, geographic information systems (GIS) represent useful tools for the synthesis of different input data and variables using specific logical and mathematical relations to produce flood susceptibility maps. The flood causative criterion (input data) employed in this study include; soil data, slope data, land use/land cover data, precipitation data, flow length data, river distance data, drainage density data, topographic wetness index (TWI) data, normalized difference vegetation index (NDVI) data, road distance data, and elevation data. The susceptibility class including the ranges and rating of each criterion is presented in Tables 1 and 2 respectively

Table 1: Flood causative criterion and their susceptibility class

Flood Causative Criterion	Unit	Class	Susceptibility Class Ranges and Rating	Susceptibility Class Rating	Weight (%)
TWI	Level	3.12-6.47	Very Low	1	
		6.48-8.39	Low	2	
		8.40-10.98	Moderate	3	
		10.99-14.49	High	4	
		14.50-24.43	Very High	5	
Elevation	M	-1-53	Very High	5	
		54-91	High	4	
		92-131	Moderate	3	
		132-194	Low	2	
		195-306	Very Low	1	
Slope	%	< 2.15	Very High	5	
		2.16-4.15	High	4	
		4.16-6.59	Moderate	3	
		6.60-10.46	Low	2	
		10.47-36.52	Very Low	1	
Precipitation	mm/yr	< 8.59	Very Low	1	
		8.60-9.28	Low	2	
		9.29-10.03	Moderate	3	
		10.04-10.74	High	4	
		10.77-11.83	Very High	5	

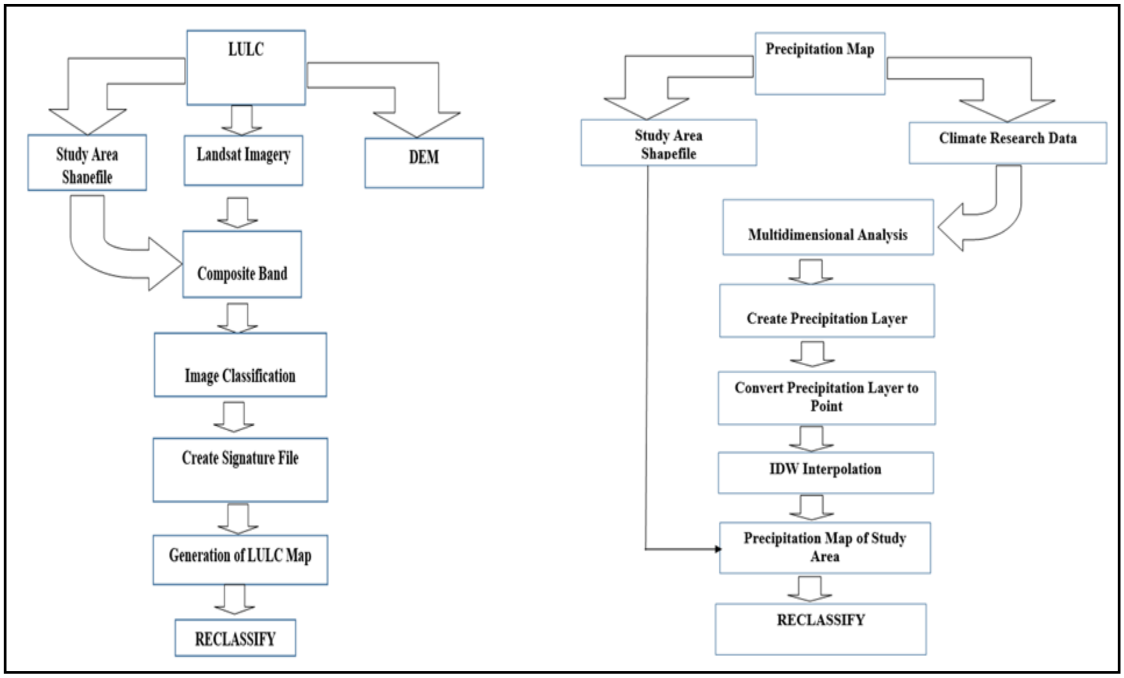
Table 2: Flood causative criterion and their susceptibility class cont.

Flood Causative Criterion	Unit	Class	Susceptibility Class Ranges and Rating	Susceptibility Class Rating	Weight (%)
LULC	Level	Water Body	Very High	5	
		Built up Area	Moderate	3	
		Barren Land	Low	2	
		Vegetation	Very Low	1	
NDVI	Level	-0.061-0.101	Very High	5	
		0.102-0.189	High	4	
		0.190-0.270	Moderate	3	
		0.271-0.348	Low	2	
		0.349-0.735	Very Low	1	
Distance From River	m	< 453	Very High	5	
		454-907	High	4	
		908-1314	Moderate	3	
		1315-1939	Low	2	
		1940-3988	Very Low	1	
Distance From Road	m	< 25	Very High	5	
		26-50	High	4	
		51-100	Moderate	3	
		101-150	Low	2	
		> 150	Very Low	1	
Drainage Density	m	< 0.733	Very Low	1	
		0.734-1.316	Low	2	
		1.317-1.917	Moderate	3	
		1.918-2.707	High	4	
		2.708-4.793	Very High	5	
Soil Type	Level	Silty Clay	Very High	5	
		Silty Sediments	Moderate	3	
		Sandy Clay Sand	Low	2	

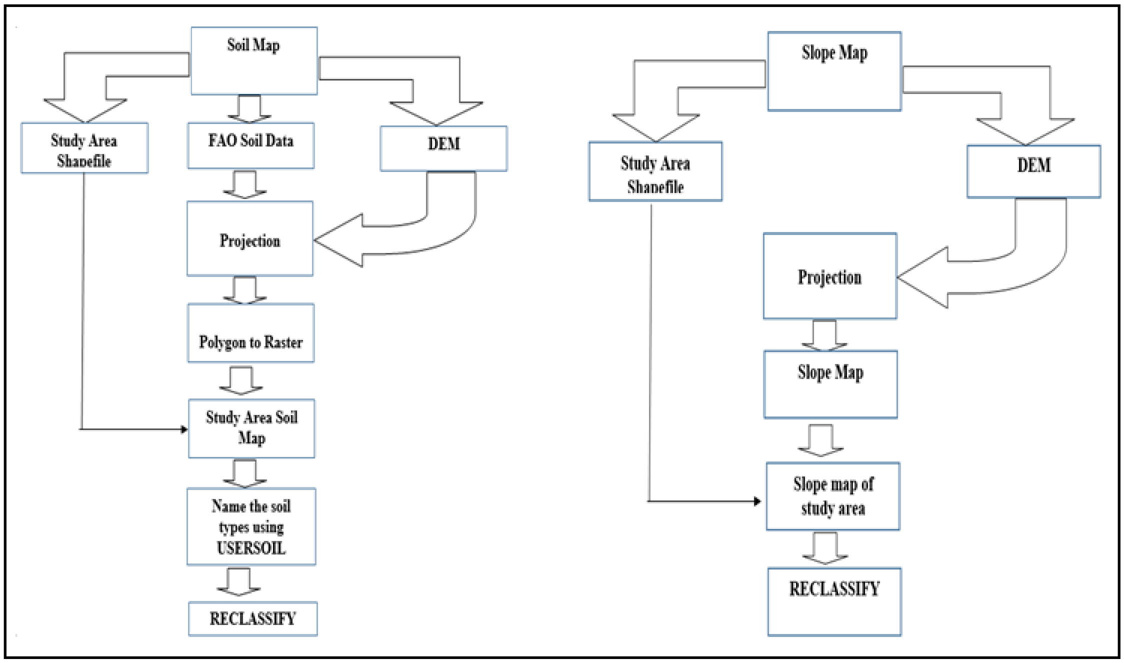
To compute the weight (%) for each criterion, analytical hierarchy process (AHP) was employed.

2.3 Procedure for Data Collection

The input data were generated in raster format using ArcGIS version 10.4.1. The step-by-step methodology employed to generate the various raster data is shown in the schematics presented in Figures 2 – 6 respectively.



Figures 2: Schematic for generating lulc map and precipitation map



Figures 3: Schematic for generating soil map and slope map

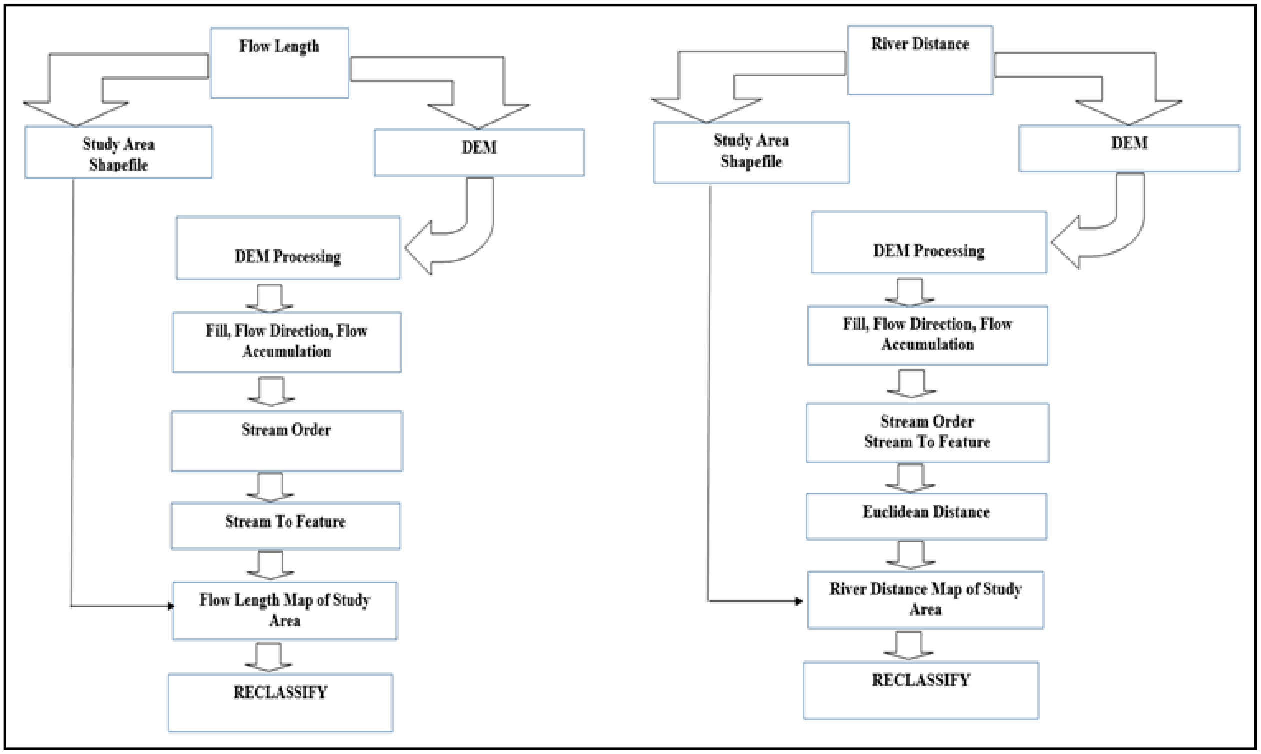
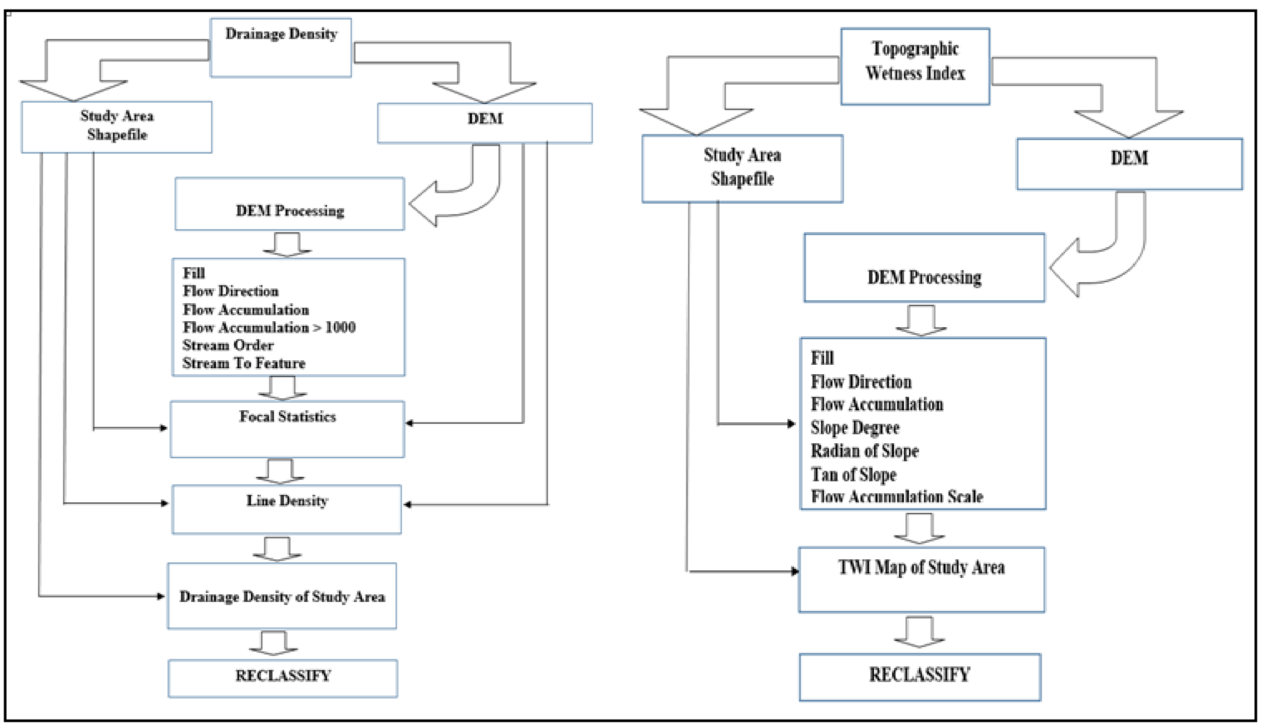
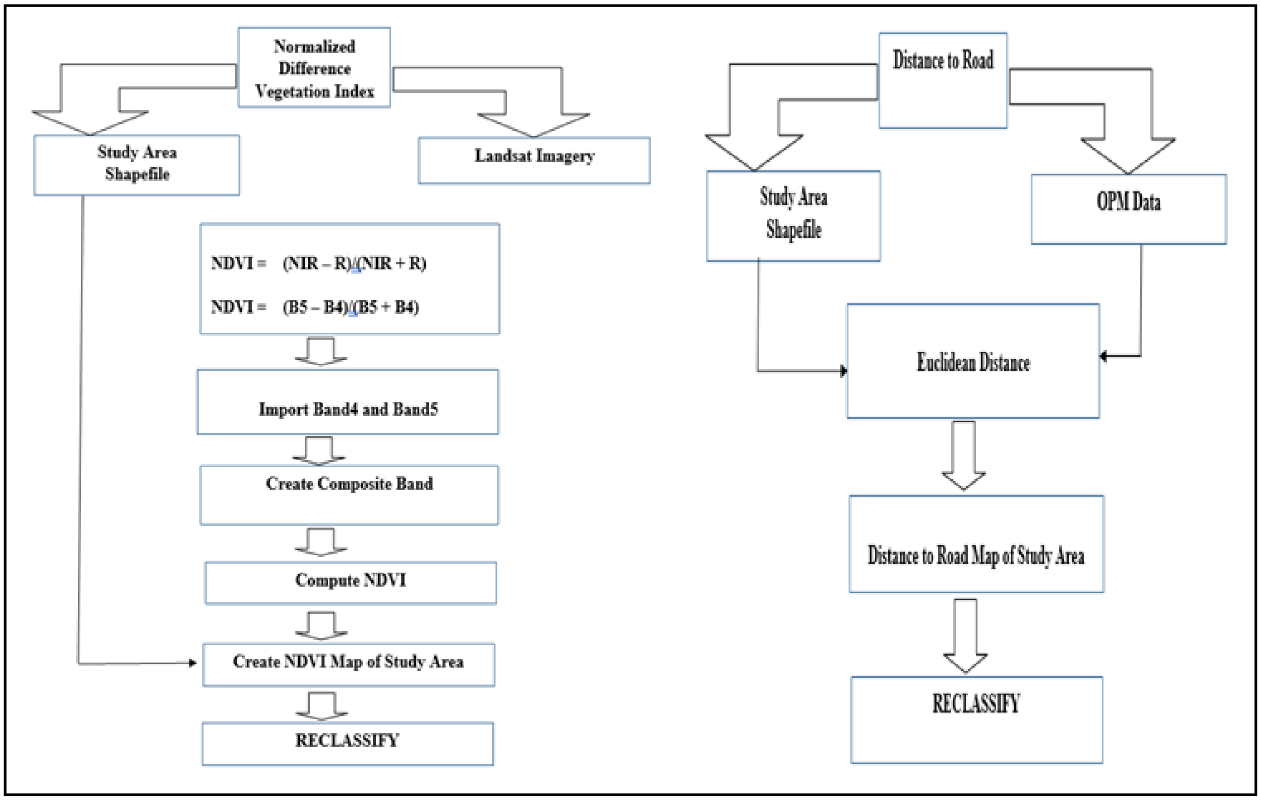


Figure 4: Schematic for generating Flow Length and river distance map



Figures 5: Schematic for generating Drainage Density and Topographic Wetness Index maps



Figures 6: Schematic for generating NDVI and Distance to road maps

2.4. Generation of flood susceptibility map using AHP and weighted overlay

In order to arrive at a final flood susceptibility map, the following thematic maps (TWI, Precipitation, LULC, Slope, Elevation, drainage density, soil, NDVI, distance from road, and distance from river) were overlayed using weighted overlay analysis. Weighted overlay analysis is a simple and straightforward method for a combined analysis of multi class maps. The weight of influence for each factor was computed statistically using analytical hierarchy process (AHP). The first step in obtaining the AHP design was to define the criteria and the sub-criteria. Table 3 presents the selected criteria and their respective sub-criteria's.

Table 3: Definition of criteria and sub-criteria for AHP analysis

Criteria	**Sub-Criteria TWI**	**Sub-Criteria Elevation**	**Sub-Criteria Slope**	**Sub-Criteria Precipitation**	**Sub-Criteria LULC**	**Sub-Criteria NDVI**	**Sub-Criteria DfRiv**	**Sub-Criteria DfRoad**	**Sub-Criteria Drain Den**
TWI	Elevation	Slope	Precipitation	LULC	NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type
Elevation	Slope	Precipitation	LULC	NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type	LULC
Slope	Precipitation	LULC	NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type		
Precipitation	LULC	NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type			
LULC	NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type				
NDVI	Distance from River	Distance from Road	Drainage Density	Soil Type					
Distance from River	Distance from Road	Drainage Density	Soil Type						
Distance from Road	Drainage Density	Soil Type							
Drainage Density	Soil Type								
Soil Type									

2.5 Definition of parameters significance scale

To define the one to nine scale of parameter significance, the scheme proposed by Saaty, reported in Table 4 was employed to translate linguistic judgments into numbers.

Table 4: Saaty summary

Sig. Strength	Explanation	Comments
1	Equal significance	Two elements contribute equally to the objective
3	Moderate significance	Judgment slightly favours one element over another
5	Strong significance	Judgment strongly favours one element over another
7	Very strong significance	Judgment strongly favours one element over another, its dominance is demonstrated by experience
9	Maximum significance	The dominance of one element over another is demonstrated and absolute
2, 4, 6, 8	Can be used to express intermediate values	

2.6 Generation of AHP Matrix

To generate the AHP matrix needed to compute the percentage weight of influence for each of the flood causative criterion, a review of previous related research work was done in order to ascertain the superiority of each criterion over the other. Result of the review is presented in Table 5 while the generated AHP matrix is presented in Table 5.

Table 5: Superiority of selected criterion

Pairwise Comparison of Maps	Relative Importance	Relative Magnitude
TWI vs Elevation	TWI = Elevation	1
TWI vs Slope	TWI = Slope	1
TWI vs Precipt.	TWI = Precipt.	1
TWI vs Lulc	TWI > Lulc	3
TWI vs NDVI	TWI > NDVI	5
TWI vs DfRiv	TWI = DfRiv	1
TWI vs DfRoad	TWI > DfRoad	3
Elevation vs Slope	Elevation = Slope	1
Elevation vs Precipt.	Elevation = Precipt.	1
Elevation vs Lulc	Elevation > Lulc	2
Elevation vs NDVI	Elevation > NDVI	3
Elevation vs DfRiv	Elevation = DfRiv	1
Elevation vs DfRoad	Elevation > DfRoad	3
Slope vs Precipt.	Slope = Precipt.	1
Slope vs Lulc	Slope > Lulc	3
Slope vs NDVI	Slope > NDVI	3
Slope vs DfRiv	Slope < DfRiv	0.5
Slope vs DfRoad	Slope = DfRoad	1
Slope vs Soil	Slope > Soil	5
Precipt. vs Lulc	Precipt. > Lulc	3
Precipt. vs NDVI	Precipt. > NDVI	3
Precipt. vs DfRiv	Precipt. > DfRiv	2
Precipt. vs DfRoad	Precipt. > DfRoad	3

Precipt. vs Drain Den	Precipt.> Drain Den	3
Lulc vs NDVI	Lulc = NDVI	1
Lulc vs DfRiv	Lulc < DfRiv	0.5
Lulc vs DfRoad	Lulc > DfRoad	5
Lulc vs Soil	Lulc > Soil	3
NDVI vs DfRiv	NDVI < DfRiv	0.5
NDVI vs DfRoad	NDVI = DfRoad	1

To validate the AHP results, the index of consistency was employed. The principal eigenvalue ($\lambda_{\max}$) is a function of the matrix divergence from consistency. In other words, a pairwise matrix is considered consistent only when $\lambda_{\max}$ equal or more than the number of the layers examined. The index of consistency was estimated using the mass balance equation of the form

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n-1} \qquad (1)$$

Where; $\lambda_{\max}$ denotes the principal eigenvalue, and n represent the number of parameters. For a 3 by 3 matrix, the consistency index is less than 0.05. For a 4 by 4 matrix, it is 0.09 while for large matrices, it is 0.1. If it matches, then the pairwise comparison is said to be consistent and the calculated weight of influence is said to be valid. The generated matrix based on AHP procedure is presented in Table 6.

Table 6: Generation of AHP matrix

Criteria	**TWI**	**Elevation**	**Slope**	**Precipt.**	**LULC**	**NDVI**	**DfRiver**	**DfRoad**	**Drain Den**	**Soil Type**
TWI	1	1	1	1	3	5	1	3	1	3
Elevation	1	1	1	1	2	3	1	3	1	3
Slope	1	1	1	1	3	3	½	1	1	1
Precipitation	1	1	1	1	3	2	2	3	3	7
LULC	1/3	½	1/3	1/3	1	1	½	5	1	3
NDVI	1/5	1/3	1	½	1	1	½	1	½	1
Distance from River	1	1	2	½	2	2	1	5	1	3
Distance from Road	1/3	1/3	1	1/3	1/5	1	1/5	1	½	½
Drainage Density	1	1	1	1/3	1	2	1	2	1	3
Soil Type	1/3	1/3	1	1/7	1/3	1	1/3	2	1/3	1

3.0Results and Discussion

3.1 Result of Drainage Density Estimation

The exact study area was estimated as 2579.18km^2. The descriptive statistics of the stream length is presented in Table 7.

Table 7: Descriptive statistics of stream length

S/n	Parameters	Computed Values
1	Mean	1.348905024
2	Standard Error	0.030877189
3	Median	1.00536
4	Mode	0.0436856
5	Standard Deviation	1.173739384
6	Sample Variance	1.377664141
7	Kurtosis	4.334600728
8	Skewness	1.716128524
9	Range	9.4495596
10	Minimum	0.0308904
11	Maximum	9.48045
12	Sum	1949.167759
13	Count	1445

From the result of Table 7, the total stream length was estimated as 1949.167712km. Using the ratio of total stream length to study area, the drainage density of the study area was estimated as 0.7557km which is classified as very high drainage density.

3.2 Map Generation and Reclassification

The generated maps and their reclassified version are presented in Figures 7 to 17.

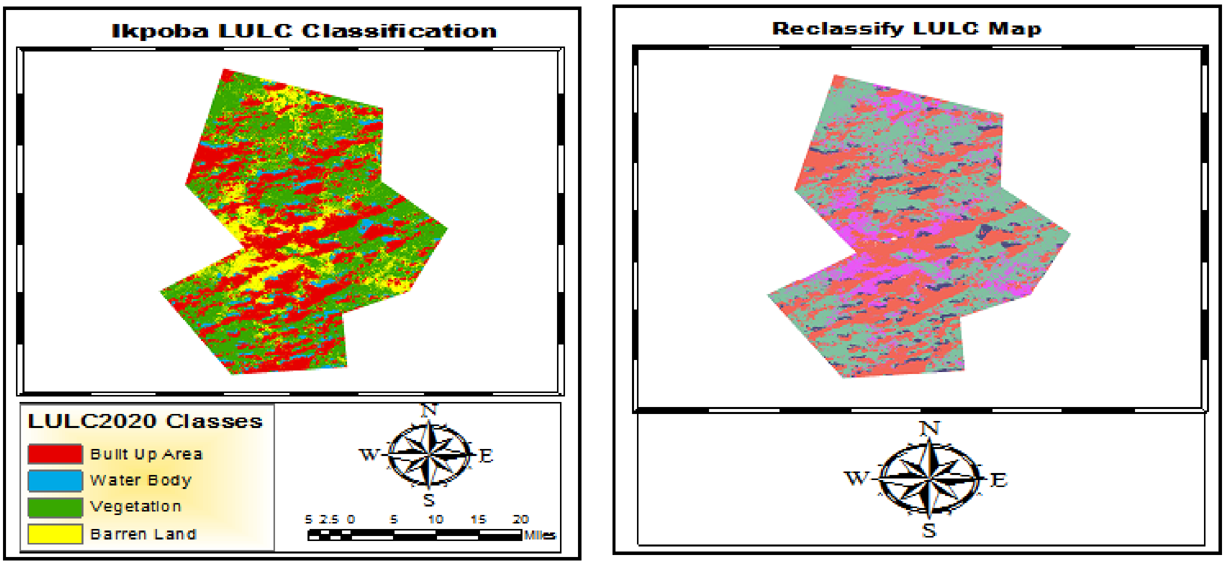


Figure 7: Ikpoba land use classification

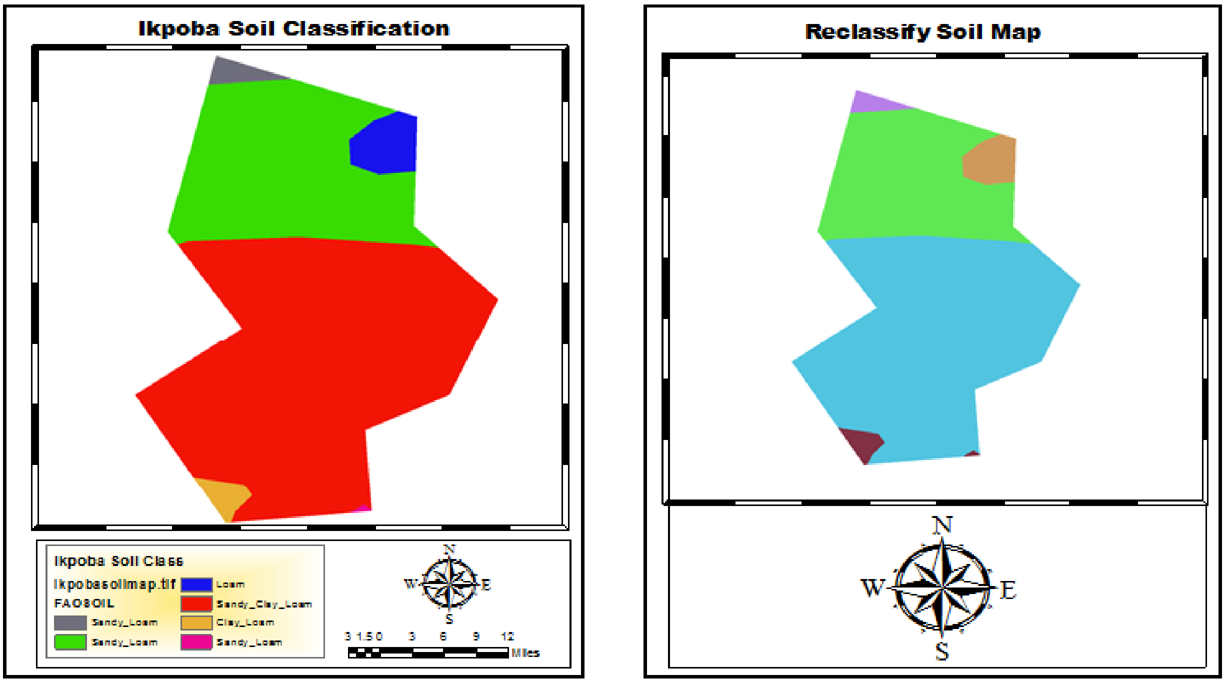


Figure 8: Ikpoba soil classification

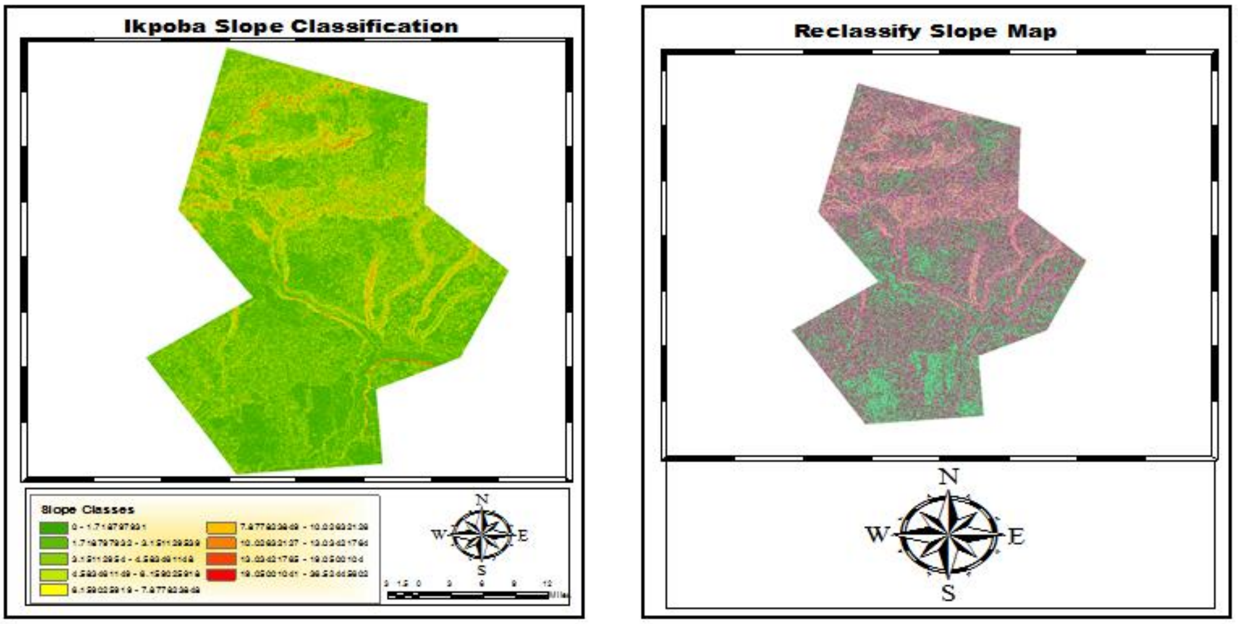


Figure 9: Ikpoba slope classification

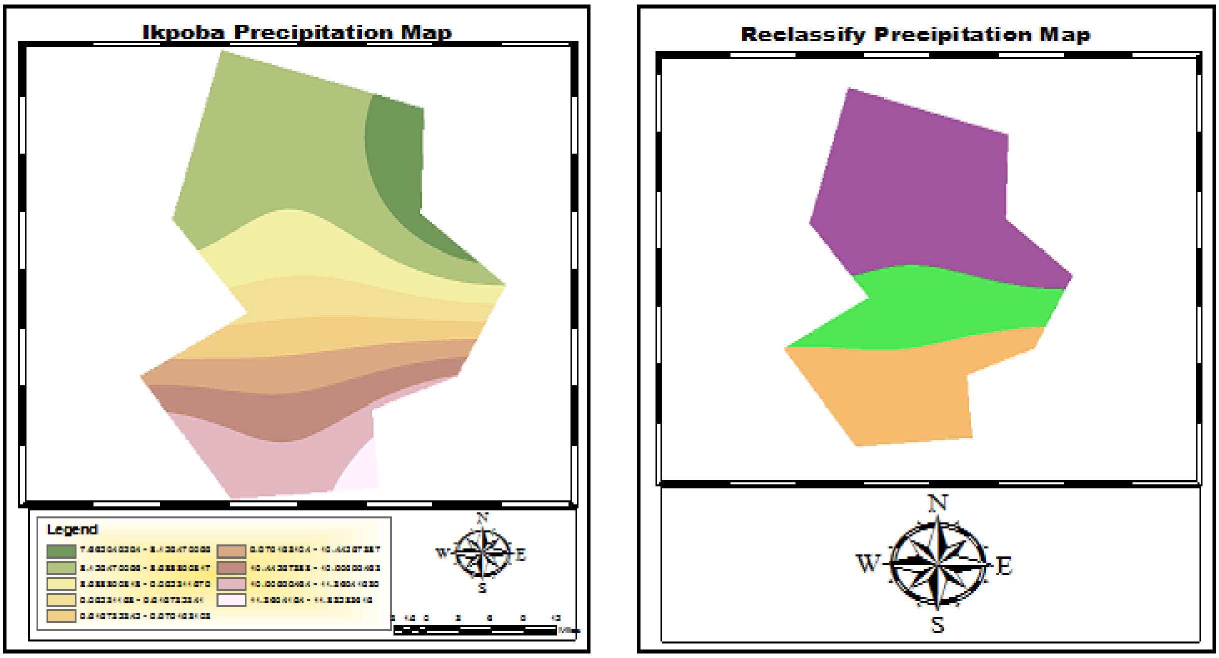


Figure 10: Ikpoba precipitation map

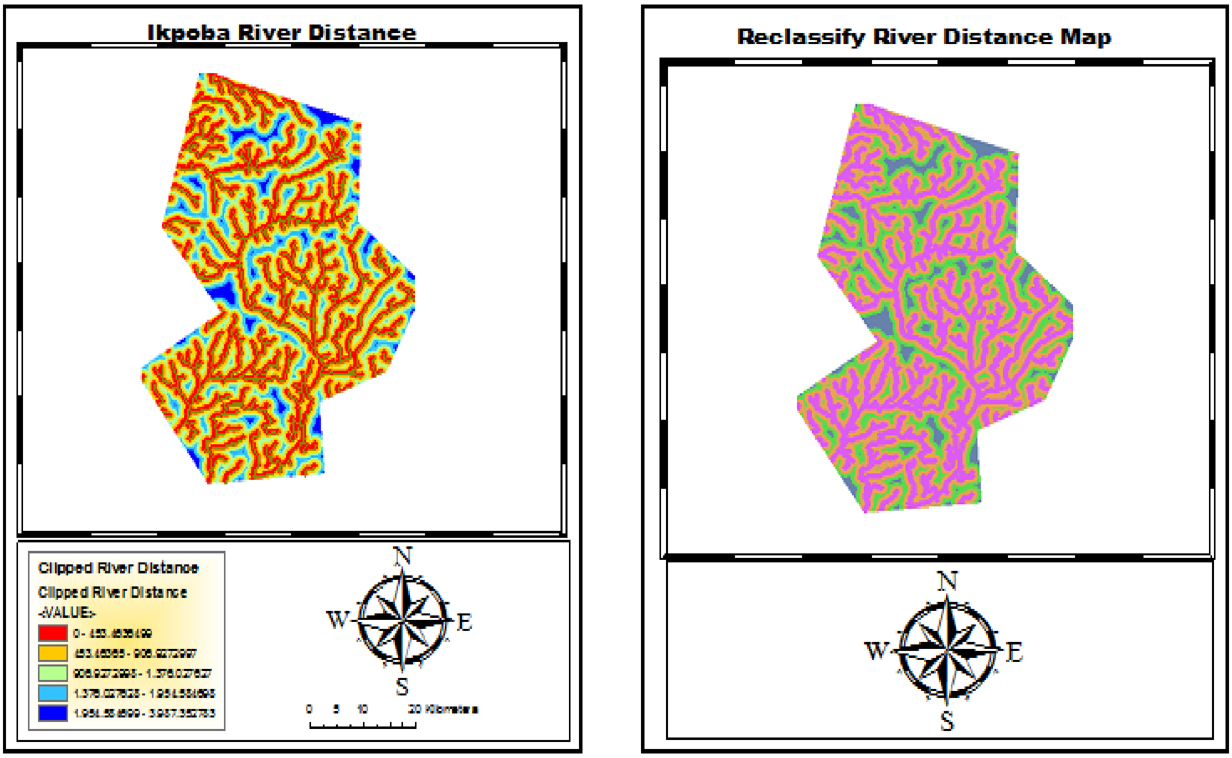


Figure 11: Ikpoba river distance map

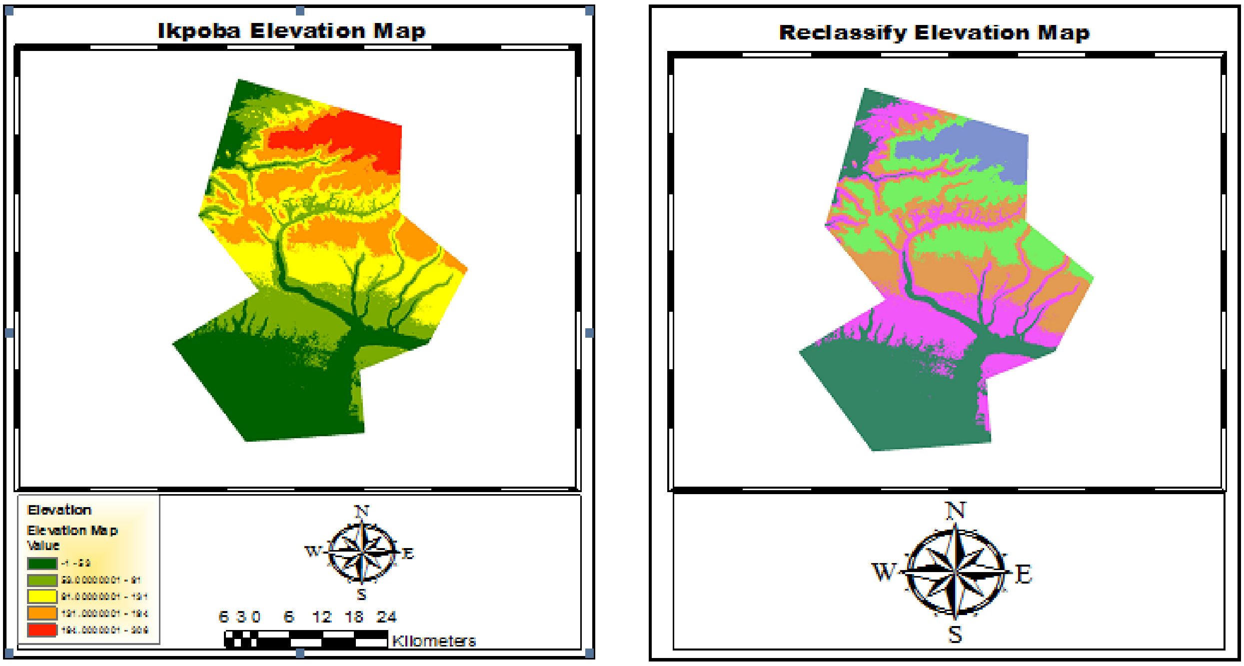


Figure 12: Ikpoba elevation classes

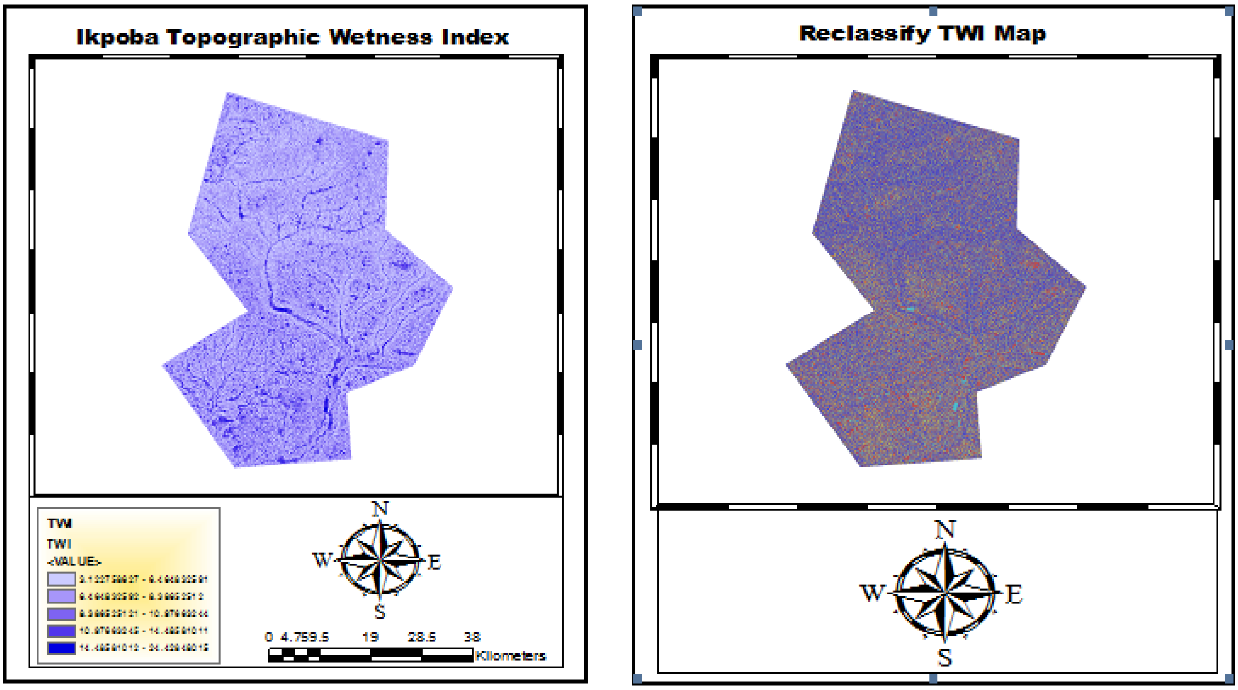


Figure 13: Ikpoba TWI classes

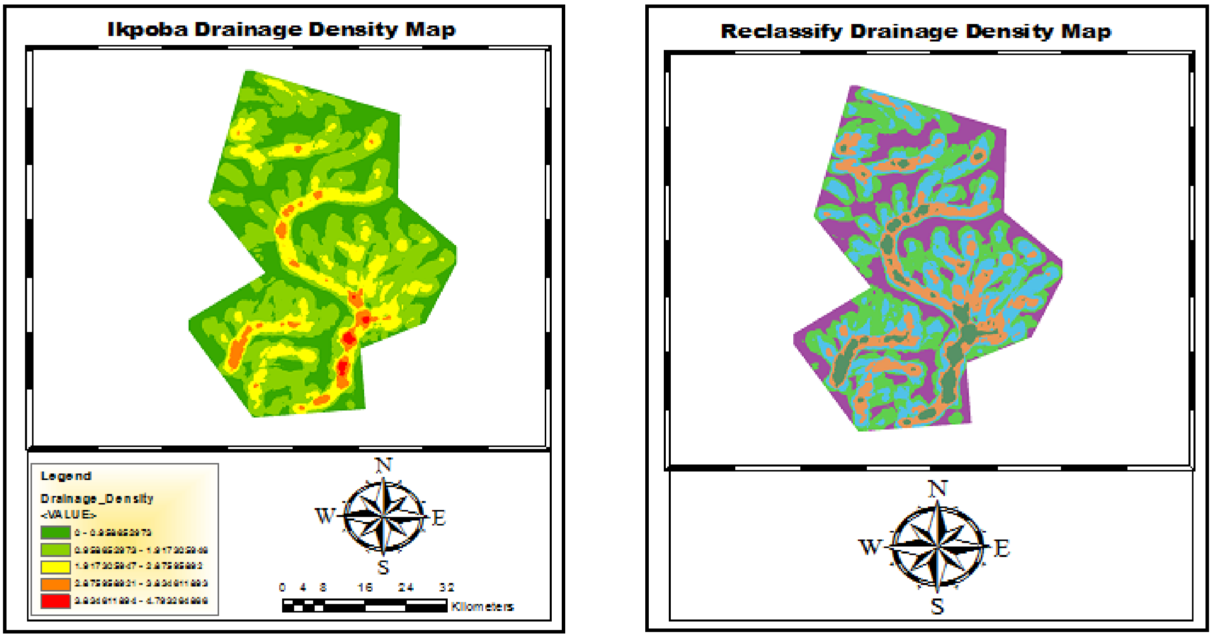


Figure 14: Ikpoba drainage density map

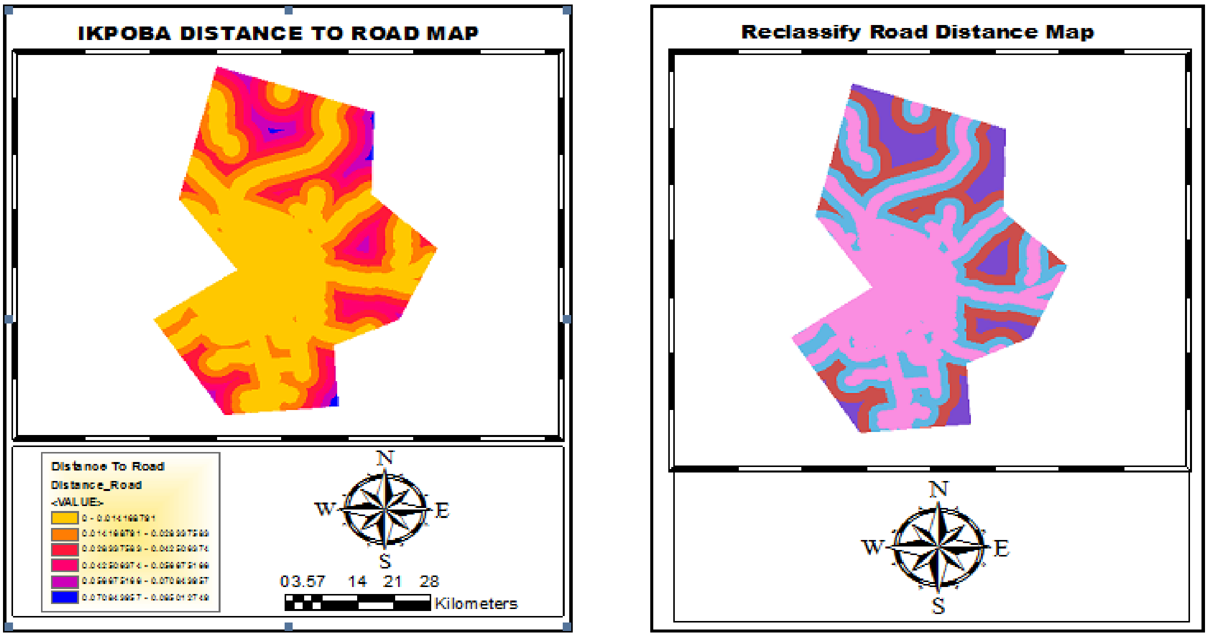


Figure 15: Ikpoba distance to road map

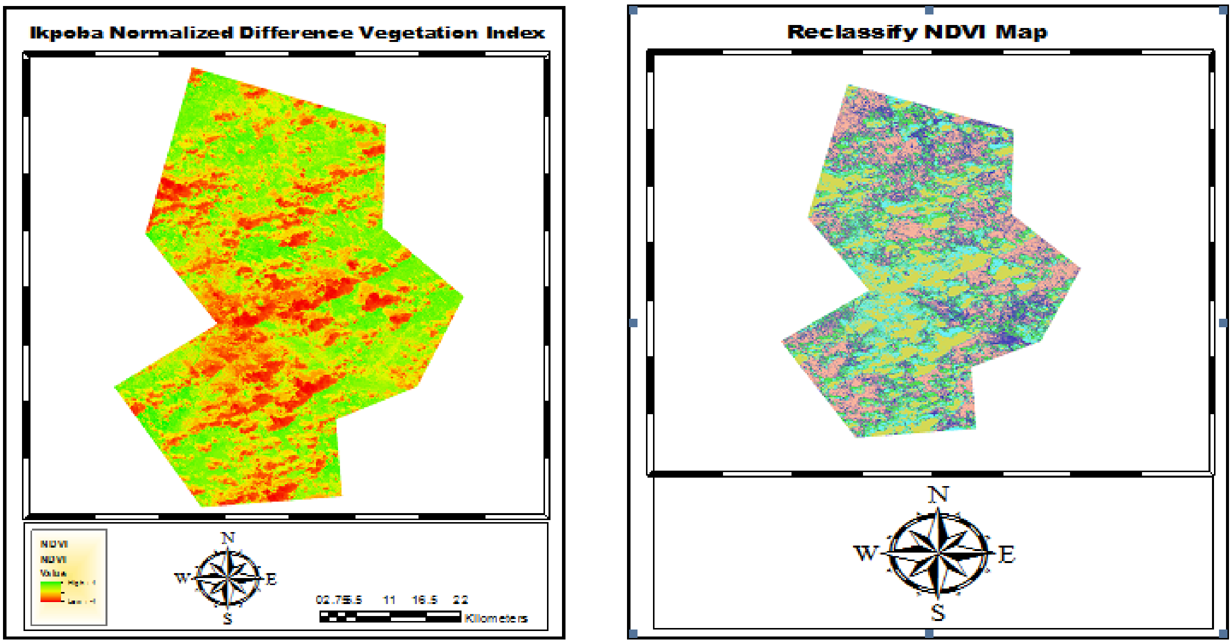


Figure 16: Ikpoba NDVI classes

Higher precipitation rate considerably increases the probability of flood. Also, higher river distance and drainage network density implies accelerated surface runoff and increases the probability of flooding since flood frequency and intensity are usually very high around drainage density areas. Particularly closer to river, higher values of topographic wetness index correspond to areas favouring water accumulation and high runoff. Topographic wetness index (TWI) is a function of both the slope and the upstream contributing area. It is also highly correlated with several soil attributes such as horizon depth, silt percentage, organic matter content and phosphorous content. In addition, TWI can also be used to quantify topographic control and terrain driven variation in soil moisture. Land use land cover change dynamic parameters usually affect hydrological process components such as infiltration, surface runoff, evaporation and evapotranspiration. For slope, elevation, distance from river and distance from road, lower values of these parameters increase the probability of flood. The normalized difference vegetation index accounts for the amount of green cover and lower values of NDVI imply higher probability of flood.

3.3 Percentage Weight Estimation using AHP

Result of percentage weight estimation using AHP approach is presented in Table 8

Table 8: Percentage of Influence for flood causative criterion

Criteria	%
TWI	14.31
ELEVATION	12.65
SLOPE	10.03
PRECIPITATION	17.48
LULC	7.82
NDVI	5.52
DISTANCE FROM RIVER	13.05
DISTANCE FROM ROAD	4.38
DRAINAGE DENSITY	10.05
SOIL TYPE	4.73

IC = 0.093 ; RC = 6.22%

With an estimated index of consistency of 0.093 as observed in Table 8, it was concluded that the pairwise comparison is consistent and the calculated weight of influence is valid. On the flood causative criterion with the highest influence, a plot of priority criterion was generated and presented in Figure 17.

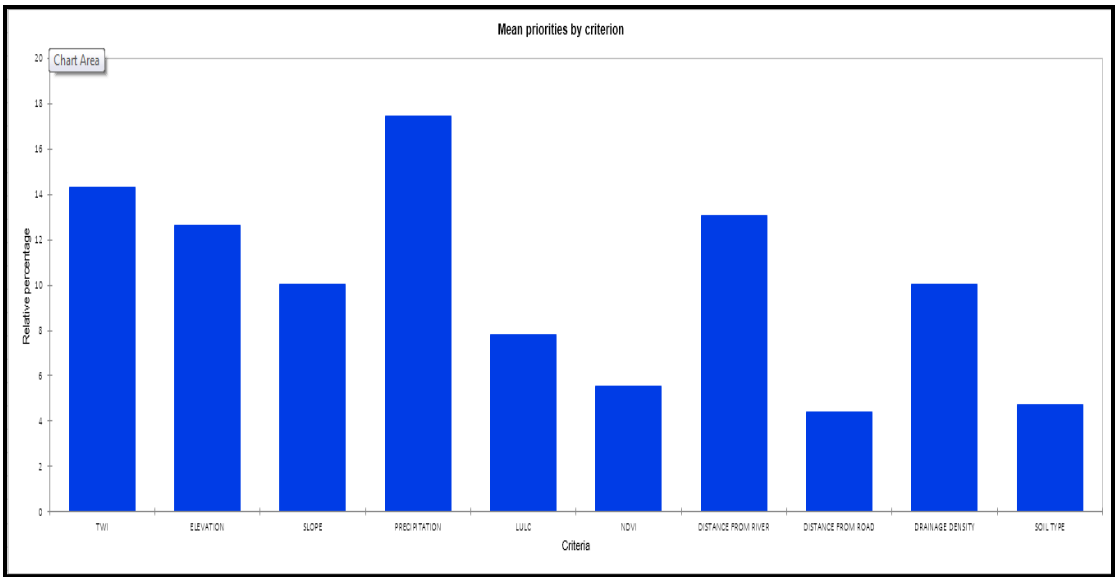


Figure 17: Percentage of infleunce of flood causative criterion

From the result of Figure 17, precipitation was acclaimed the factor with the highest influenced on flood followed by the topographic wetness index and distance from river.

3.4 Generation of Final Flood Susceptibility Map

Using the estimated percentage weight base on AHP, the weighted overlay tool in ArcGIS 10.4.1 was then employed to stack the reclassify raster data in order to generate the final flood map presented in Figure 18.

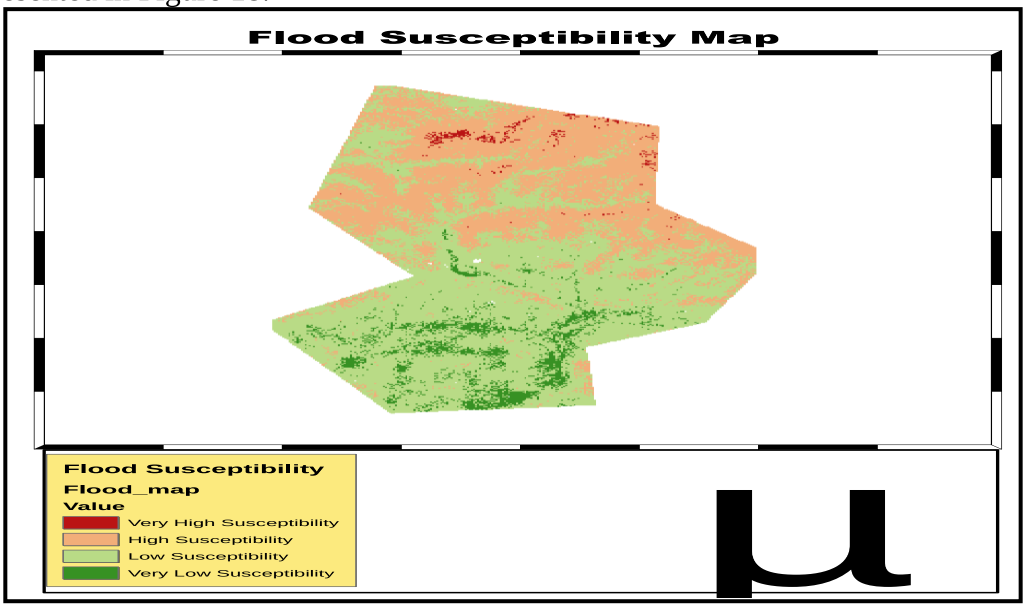


Figure 18: Final Flood Map of Study Area

In order to determine the areas with high flood risk, the flood map was converted to kml file and thereafter projected to google. The outcome is presented in Figure 19.

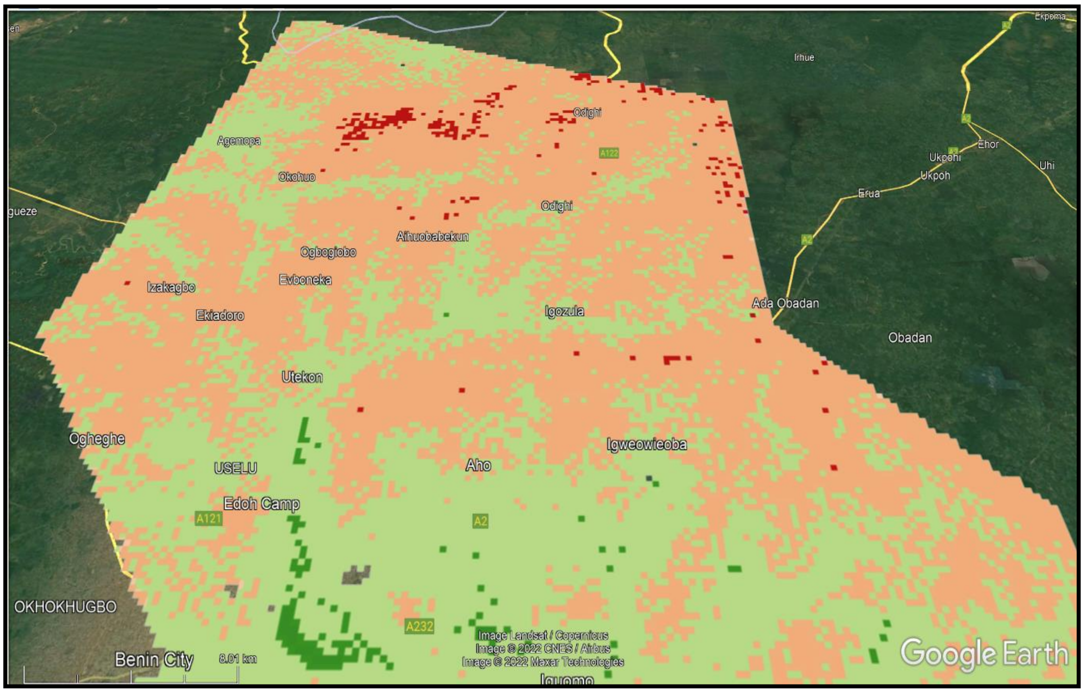


Figure 19: Projected flood susceptibility map

Based on the outcome of Figure 19, it was observed that communities such as; Odighi and Okohuo pose a very high risk of flooding while Aihuobabekun, Ogbogiobo, Evboneka, Izakagbo, Ekiadoro, Ogheghe, Uselu and Aho pose a high risk of flooding.

4.0 Conclusion

The presented study aimed to define the flood susceptibility zones for Ikpoba catchment using AHP technique and GIS. Ten flood conditioning factors were chosen in order to capture the complexity of physical configuration of the study area. The equal proportional principle for the selection of flood conditioning factors was used and the following factors were selected: Topographic wetness index (TWI), Elevation, Slope, Precipitation, and Land use land cover. Others are; Normalized difference vegetation index (NDVI), Distance from river, Distance from road, Drainage density and soil type. The AHP technique was used to calculate the factor weights based on Saaty's nine-point scale of influence. The relative importance of the selected conditioning factors prioritized precipitation as the most important factor for finding areas susceptible to flooding, followed by topographic wetness index (TWI) and distance from rivers. Finally, the weighted overlay method was employed to combine the reclassified factors and produce the resulting flood susceptibility map which contains four classes: very low, low, high, and very high susceptibility. Flood susceptibility mapping for flood prone areas provide general knowledge of the flood hazard, predict risk areas and helps in establishing flood management measures.

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