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ANALYSIS OF FLOOD SUSCEPTIBILITY IN NORTHERN ANAMBRA STATE: A GIS MULTI-CRITERIA DECISION MAKING MODEL OF AHP, BWM. AND CRITIC METHOD

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ABSTRACT

The vulnerability of the Northern region in Anambra was modelled using Analytical Hierarchical Process (AHP,) Best Worst Method (BWM) and Criteria Importance Through Intercriteria Correlation Method (CRITIC Method) by performing a pairwise comparison matrix of the nine flood influential factors with the aid of GIS. This was modelled with the aid of Geographic Information System (GIS). GIS, is a veritable software for modelling and predicting spatial aspects of the real world. Nine flood conditioning factors were used to model the flood susceptibility of Northern Anambra region. The conditioning factors for the analysis were rainfall, slope, aspect, lithology, LULC, elevation, SPI, NDVI, and drainage density. The value obtained from AHP, BWM and CRITIC method analysis indicated that 73%, 72% and 78% of the land area were susceptible to flooding, and thus implied that about 1197.89km^2 out of the 1794km^2 are liable to experience frequent flooding events. These values were validated with AUC curve, with AHP, BWM and CRITIC method having an accuracy prediction of 74%, 73% and 78% respectively at 95% level of confidence. According to the flood inventory and the modelled map, flooding is evident in the southwest, west, and south-eastern parts of the study area. Rainfall is weighted as the highest influencing factor for AHP and BWM but Aspect weighted the highest influencing factor for CRITIC method. We thus recommend that effort for provision of advanced drainage system, which will enable water to make its path to the river in the rainy season, as this will mitigate dry land being submerged in water at every rainy season.

KEYWORDS: Flood, susceptibility, Geospatial, Flood Analysis, Disaster Management, Analytical Hierarchical Process (AHP), Best Worst Method (BWM), Criteria Importance Through Intercriteria Correlation Method (CRITIC method).

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1. INTRODUCTION

Flooding is a leading cause of loss of life and property. One-third of nature's forces have been attributed to flooding (Ferreira, 2011; Sarkar and Mondal, 2020; Forson, Amponsah, Hagan, and Sapah, 2023). It is evident that the frequency of occurrence of flooding is steadily on the rise on a global scale. in recent time, the consequences of floods bore by communities worldwide amounted to an average of 60 billion dollars (UNESCO, 2021). Although, a flood-related fatality has substantially decreased in the recent decade due to flood control infrastructures; nevertheless, most developing countries are still much susceptible to these events. For instance, flood events in Nigeria between 2012 to 2016 and recent flooding in 2020 and 2022 which occurred in Nigeria and Burkina Faso claimed lives, displaced thousands of people, and destroyed infrastructure (UNESCO, 2022). Flooding impact vulnerability is wider than any other natural disaster as a result of its drain on the economy of a nation due to continual spending, population and infrastructural displacement, water-borne diseases, and loss of aquatic lives. Liu et al (2017), reported an increase in bacillary dysentery risk in Baise Guangxi Province China from 2004 to 2012 flooding. A similar flood event in Thailand caused a disruption in the food supply chain in the country (Ziegler et al., 2012; Haraguchi and Lall, 2015; Promchote et al., 2016).

Often most flooding is typically due to the hydrology of the area, recurrent and persistent rainfall. It is striking to note that in developing countries like Nigeria, flooding almost occurs repeatedly during the rainy season, causing magnified impacts such as building collapse, disruption of traffic flow, and damage to agriculture. To avert these consequences, there is a need to address the flooding menace by ensuring that there is adequate analysis of flood susceptibility for mitigation of future flooding, effective prevention strategies or early warning system (Tehrany et al., 2015; Lino et al, 2021; Okeke, Dunu, and Okafor, 2023). Geospatial technology tools and their techniques are proven to be useful in identifying flood vulnerability zones and properties. Saha et al., (2005); Wang et al (2013); Pourghasemi et al., (2014), asserted that geospatial techniques provide suitable platform to analyze and manipulate any relevant data to demarcate hazard zones easily. Furthermore, geospatial tools can access flood damages (Patel and Sirarsteara 2013) which caused by sea wave surge or excessive rainfall in the catchment area (Samanta, Pal and Palsamanta 2018).

The Northern region of Anambra State is known to experience frequent flooding. The 2012 flood event recorded a high number of loss of lives and properties of the residents among all flood incidence that has occurred in history of the state creation and other subsequent flood disasters showing potential threat. Identifying areas susceptible to flooding will aid assessment and prevention. This study aims at identifying the flood susceptibility in Northern Anambra State using geospatial tools as a decision support system.

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2. STUDY AREA

The study was carried out in Northern Anambra State. The region comprises three local government areas; which are Ayamelum, Anambra North and Anambra East (Figure 1). Its geographic periphery is between latitude 6º 13' N and 6º 45' N and longitude 6º43' E and 7º 13' E and a landmass of about 1794 Km^2. The region has a major river called Omambala River, which is a tributary of River Niger. The state experiences an annual rainfall of 1500mm - 2000mm and with considerable annual variation in temperature of about 25ºC - 29ºC in the rainy season (Ezenwaji and Otti, 2013). The Northern region of Anambra State is known for its alluvium, clay and shale geological formation. Population of the region was 477,604 in 2006 (NPC, 2006) and a projected figure of 632,000 in 2016 (NPC, 2016). It is notorious for its frequent flood phenomenon. Over the past years, it has experienced damages as a result of floods especially the 2012 and 2022 flooding which made historical consequences such as fatalities, damage to property and economic loss.

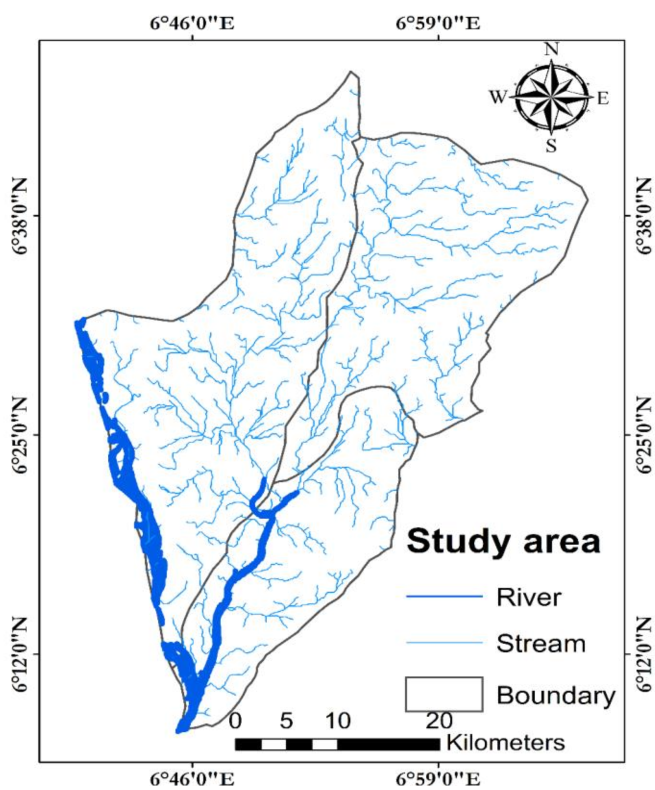

Figure 1. Map of Northern Anambra State, Nigeria.

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3. LITERATURE REVIEW

As a result of global warming, the climate in Africa and Asia is predicted to become more variable, and extreme weather events are expected to be more frequent and severe, with increasing risk to health and life. This includes an increased risk of drought and flooding in new areas (Few et al, 2004; Christensen et al, 2007; UNFCCC, 2008).

Forson, Amponsah, Hagan, and Sapah, (2023), accessed the vulnerability of the Greater Accra Region of Ghana to flooding by applying the frequency ratio modelling technique. The nine conditioning factors used comprise slope aspect, topographic roughness index (TRI), topographic positioning index (TPI), stream power index (SPI), sediment transport index (STI), profile curvature, LS factor, rainfall and drainage density. The flood vulnerability model (FVM) was discretized into five classes of very high (751.33 km^2), high (333.19 km^2), moderate (387.88 km^2), low (479.33 km^2) and very low (1590.55 km^2) zones.

Natarajan et al (2021), used ten (10) variables (land use/land cover, elevation, slope, topographic wetness index, surface runoff, landform, lithology, distance from the main river, soil texture and soil drainage) for flood susceptibility mapping using frequency ratio model for the 88 micro watersheds of Adyar, Cooum and Kosasthalaiyar watersheds of Chennai Corporation area. The developed frequency ratio was varied from 0 to 27.11 and reclassified into five flood vulnerability zones namely, very low (less than 5.0), low (5.0 7.5), moderate (7.5–10.0), high (10.0–12.5) and very high susceptibility (more than 12.5). The result revealed that 10.48 and 38.93 percentage of the land have very high and highly vulnerable class, respectively.

In an attempt to delineate flood vulnerability areas for Kulik River basin through frequency ratio model, Sarkar and Mondal (2020) used 9 parameters namely slope, elevation, rainfall, drainage density, land use–land cover, TWI, population density, road density and household density for understanding flood mechanism. Flood vulnerability zone map yielded an outcome that was classified into five zones such as very low (2.02 km^2), low (2.45 km^2), moderately low (2.44 km^2), highly vulnerable (2.26 km^2) and very highly vulnerable (1.21 km^2) areas.

Njoku, Efiong, and Ayara (2020), studied local government areas (LGAs) in Nigeria that are at risk and vulnerable to flooding. The study incorporated multi-criteria approach and geospatial techniques. Four (4) factors considered were elevation, slope, rainfall intensity, and distance to river. The result revealed that nineteen (19) states and 114 LGAs face high risks, especially communities in the Niger Delta, around the lagoons of Lagos, along River Niger, Benue, and the Cross-River. Also, 125 LGAs in 18 states face medium flood-risk vulnerability. Communities exposed to high flood-risk vulnerability also include Rivers, Kogi, Cross River, Akwa-Ibom, Delta and Anambra. In Anambra State, flood occurrence is

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frequent and has become an annual event. Studies on flooding in Nigerian cities have concentrated on typologies, underlying determinants and consequences. Abubakar (2012) described floods as the most common and widespread of all-natural disasters throughout Nigeria, of which he cited that the Ibadan flood of September 2011, claimed over 120 lives and left thousands displaced; while the Lagos flood claimed about 25 lives, with more than 1000 people displaced in July 2011. Also, the Sokoto flood-displaced 130,000 people in September 2010; six died with 276 displaced in the Kano flood in June 2011. The National Emergency Management Agency (NEMA, 2012) reported that the 2012 flood in Nigeria was declared a national disaster as it affected over 2.3 million people and killed over 363 people. Several Nigerian cities were submerged by the flood and affected 34 out of 36 states of the federation including Anambra State which was ranked as the worst hit. According to NEMA (2012), at least 68 people were killed in Plateau State in central Nigeria and also 25 bodies were found in Benue River after the flood while properties were also lost. These occurrences show that flooding is ailing the affected national populace and economy; yet mitigation measures are still poor as affirmed by the Anambra State Ministry of Environment (2012) (ANSEMA, 2012). Anambra State was declared in 2012 as the most affected state by the flood of 2012.

In Anambra State, rainfall figures recorded in 2012 show a clear departure from the normal (Abbey and Nwankwo, 2012; Anambra State Ministry of Agriculture, 2012). The climate change phenomenon with its associated increase in global temperature, precipitation and rise in sea levels has also ushered in an increased frequency of flooding in recent times. In the year 2012, many Nigerian cities suffered from the ravaging effects of flooding. This led to loss of lives, internal displacements, destruction of properties, disruption of socio-economic, cultural and religious activities; and splintering of family ties. The cities of Awka and Onitsha in Anambra State, Nigeria featured among the vulnerable cities which are susceptible to flooding (Efobi and Anierobi, 2013). Etuonovbe (2011) concluded that globally, flooding has displaced more people than any other hazard or disaster. About 20% of the Nigerian population is at risk of flooding. Etuonovbe (2011) and Ndukuba (2023) acknowledged flooding as a perennial problem in Nigeria which consistently causes death and displacement of communities. In 2010, about 1,555 lives were lost and 258,000 more displaced, while properties worth billions of naira were destroyed. In October 2022, Nzeagwu reported in the Guardian (2022) that 651, 053 persons were rendered homeless by flood in different wards in Anambra State. According to the record from the State Emergency Management Agency (as reported by Ndukuba 2023) on communities affected by the 2022 flood in Anambra, Ogbaru had 286,000 displaced persons, Anambra West had 237,000, Anambra East 103,000, Awka North had 10,345 victims, while Anyamelum had 9,240 flood cases with 5,468 displaced persons.

Taoheed (2022) reporting for Tribune on the 2022 flood stated that a family of six persons drowned to death by flood in Nzam community in Anambra East Local Government Area of Anambra State. Osibe (2022) in a similar report stated that the number of refugees in the eight local councils affected by flood hit 14,000 people, while the death toll rose to 17.

Ezenwaji and Otti (2013), examined rainfall direction and flood implication in Northern Anambra State. The application of Multi Criteria Decision Making (MCDM) is used by scientists to solve problems and predict outcomes. In flood susceptibility, MCDM, has been employed widely in decision making. Okwu-Delunzu et al., (2017) spatially assessed flood vulnerability of Anambra East using GIS and Remote Sensing (RS). Nachuppa et al., (2020) employed AHP and ANP model in analysing flood susceptibility in Salzburg, Austria. Chukwuma et al (2021), integrated GIS and IVFRN-DEMATEL-ANP model to delineate the vulnerability zones in Anambra. They employed weighted linear combination (WLC) approach for their decision making. This involves the derivation of composite map for flood vulnerability areas. Pathan et al., (2023). Integrated AHP, Fuzzy AHP, WLC, ordered weighted average and local weighted linear model for decision making. This paper integrated AHP, Linear Best Worst Method (LBWM) and Criteria Importance Through Intercriteria Correlation Method (CRITIC) for modelling flood susceptibility which has not been applied for flood susceptibility. CRITIC method is specialized to serve multiple objectives at the same time, by composing subjective and objective weights in an index of overall importance. It has been successful in providing reliable results~~.~~ (Anand et al., 2022). Liu and Zhao (2013) conducted a subjective and objective study by accumulating AHP and CRITIC method. Their proposed study evaluated the index weights, which was found to be based on subjective and objective information. BWM has two method BWM (non-linear) and BWM (linear). BWM method is a multicriteria decision making which employs the technique of analysing the best and worst method for decision making.

4. DATA AND METHODOLOGY

Since we aim to employ geospatial technology in Analytical Hierarchical Process (AHP), BWM and CRITIC analysis, we utilised the geospatial analytics procedure via the collection of geospatial data. Geospatial analysis is the collection, display, and manipulation of imagery such as satellite data, GPS or historical data. Figure 2 described the data acquisition, processing and analysis flow chart of this study, which was sourced from satellite imagery, with Landsat 7 and Landsat 8 imagery; and the digital elevation model (DEM). Due to the error of shorelines which exist on Landsat 7, there was a need for corrections and rectifications.

For this study, nine influencing factors (rainfall, slope, drainage density, stream power index (SPI), Normalised Difference Vegetation Index (NDVI), lithology, land use land cover (LULC), aspect, and elevation were utilised for AHP analysis. Consistency ratio (CR), Consistency Index (CI) and Random Index (RI) was calculated and used to derive the weight assigned to the factors to produce the susceptibility map. The data analysis was processed and analysed using geospatial tools mainly ArcGIS and ENVI.

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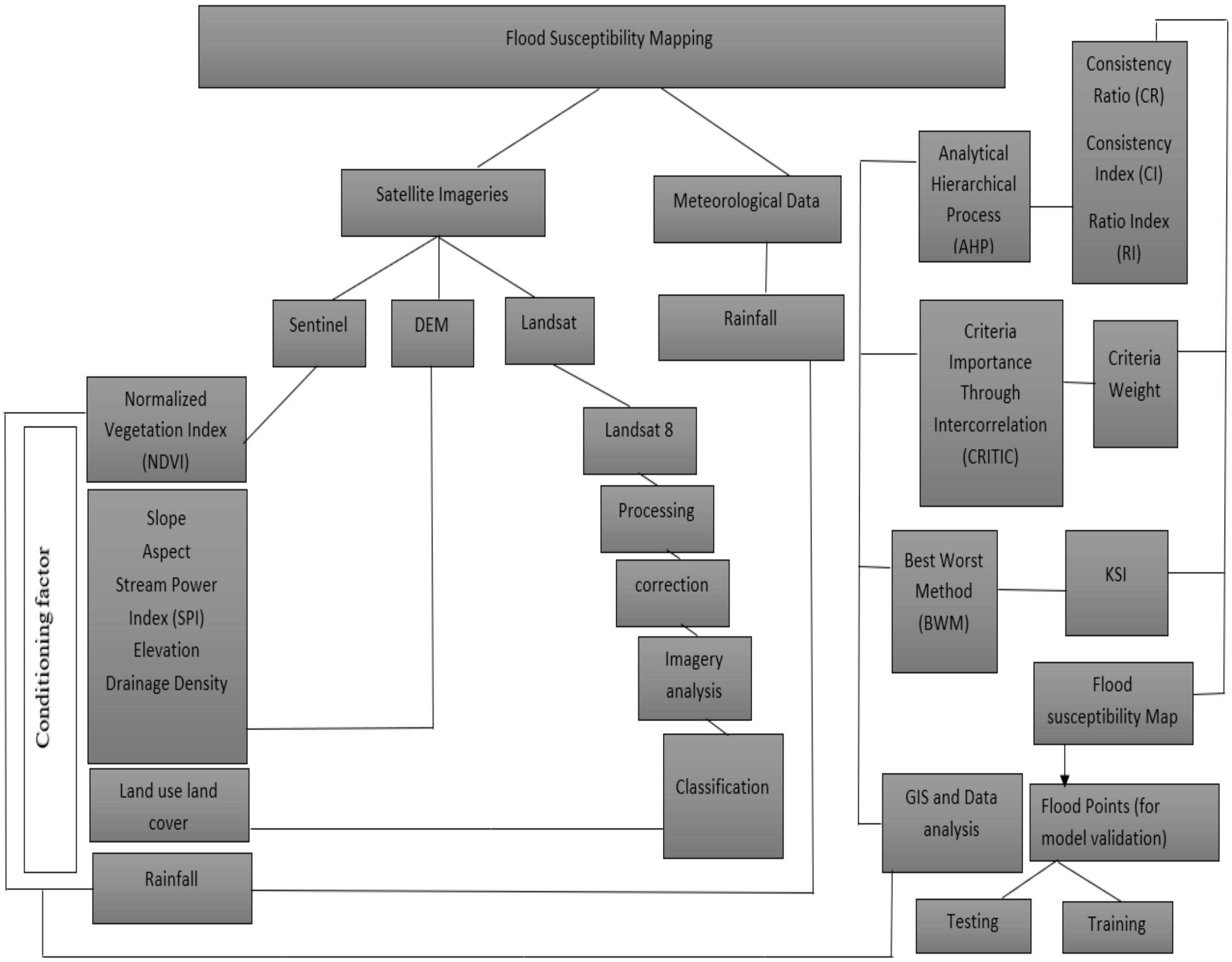

Figure 2. Chart of the methodological framework and data analysis process.

5. Analysis of Flood Influencing Factors

The flooded area either natural or anthropogenic can be accessed by some thematic factors. The runoff process and rate can be accountable by slope, and elevation. These factors often have related contributions to floods (Pourghasemi et al., 2014) and their determinants are vital for flood modelling (Sanyal and Lu, 2004). Northern Anambra zone was modelled with nine conditioning flood factors including rainfall, slope, aspect, elevation, NDVI, Stream power index (SPI), land use land cover (LULC), lithology and drainage density.

5.1 Slope:

Slope is an important factor in flood vulnerability mapping due to its influence on the runoff speed. An increase in slope leads to a decrease in infiltration rate. The slope applied in this study was derived from

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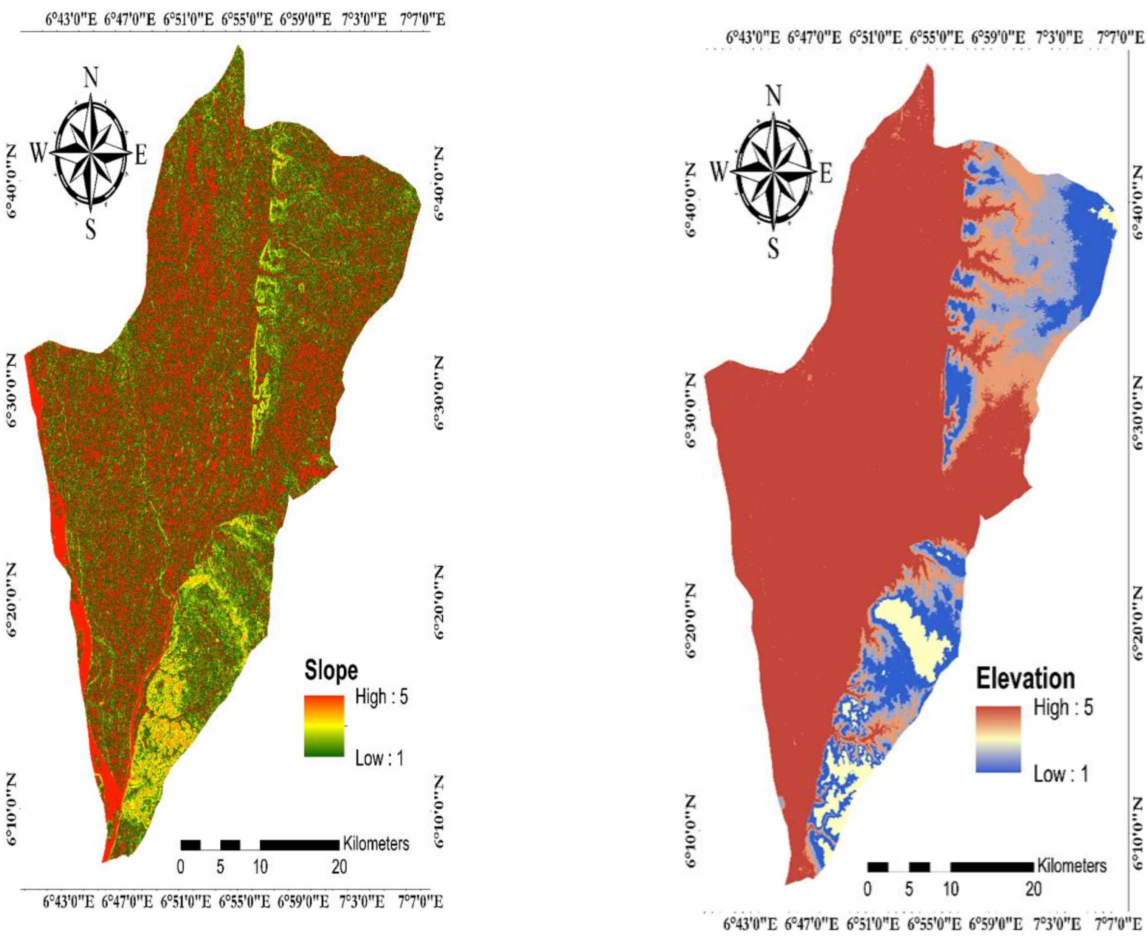
a digital elevation model (DEM) of 90m resolution and calculated in degree. The spatial distribution of slope in Northern Anambra State is illustrated in Figure 3a, which shows that areas on green and yellow colouration are high grounds/non floodable areas; they include Nkwelle Nkwelle, Ukwu Abwa, parts of Umuleri, Nando, Nsugbe, parts of high grounds of Aguleri amongst others. However, most of the towns that make up Northern part of Anambra State are susceptible to flood.



(a) (b)

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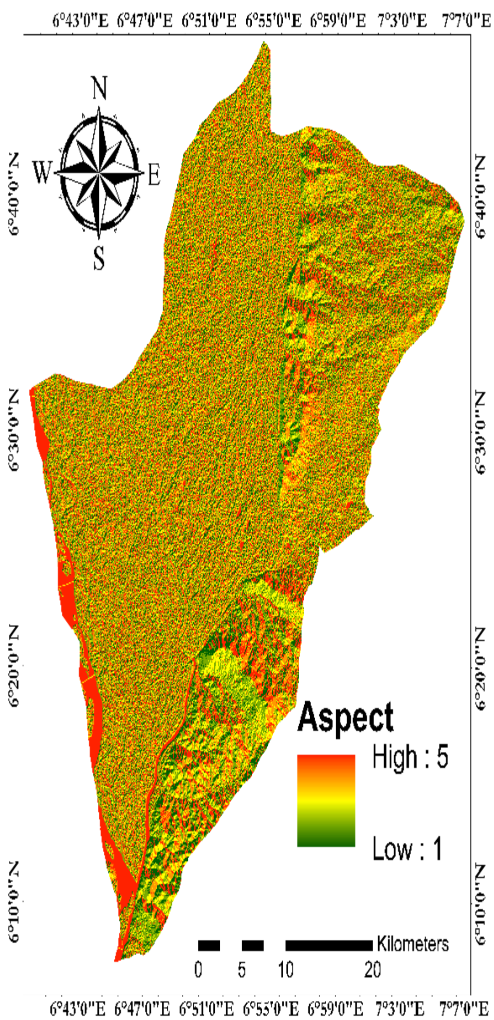

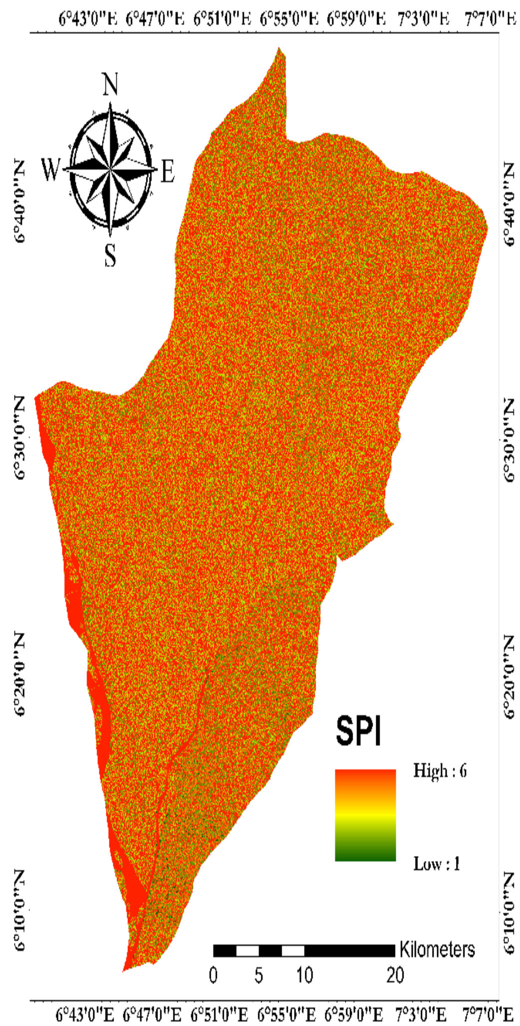

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(d)

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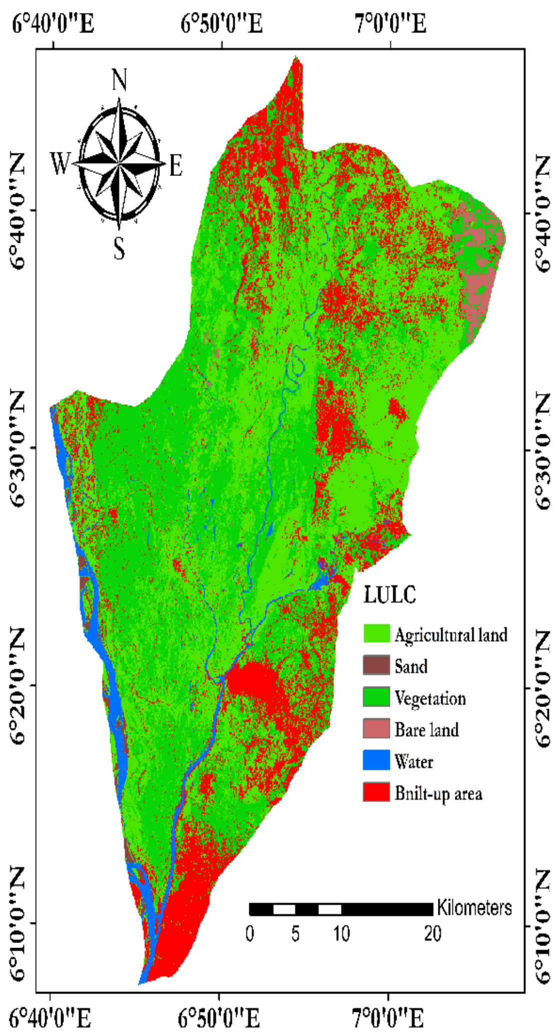

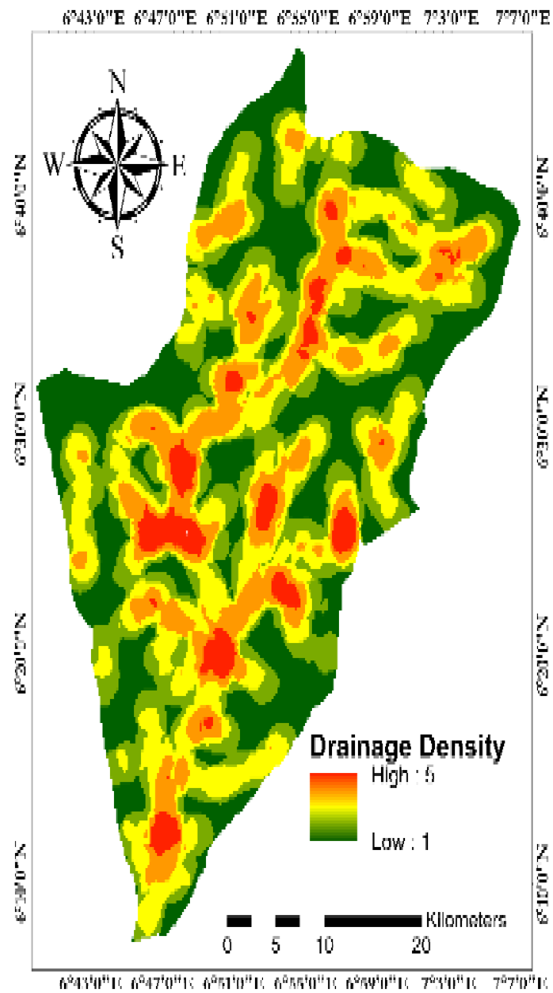

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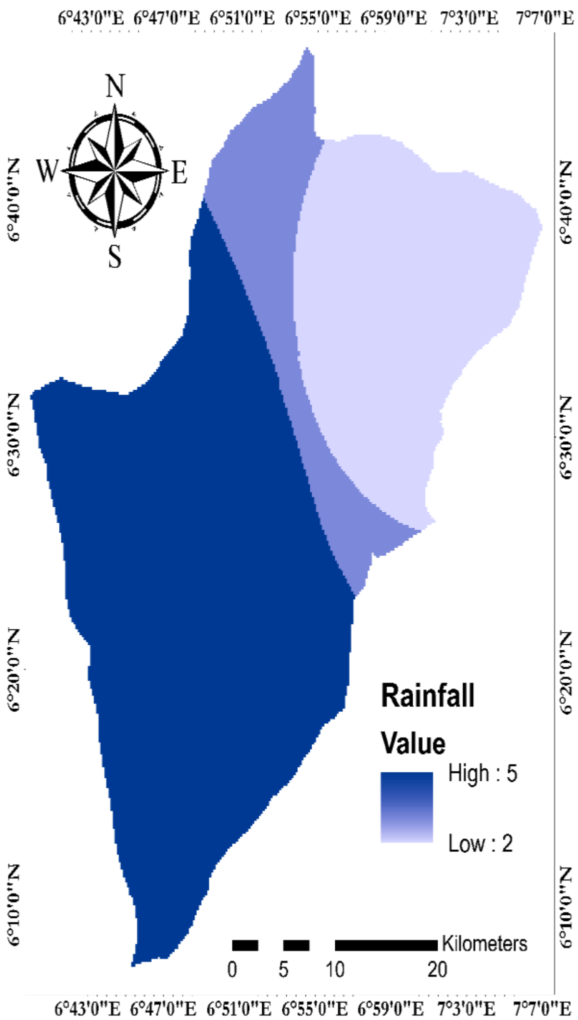

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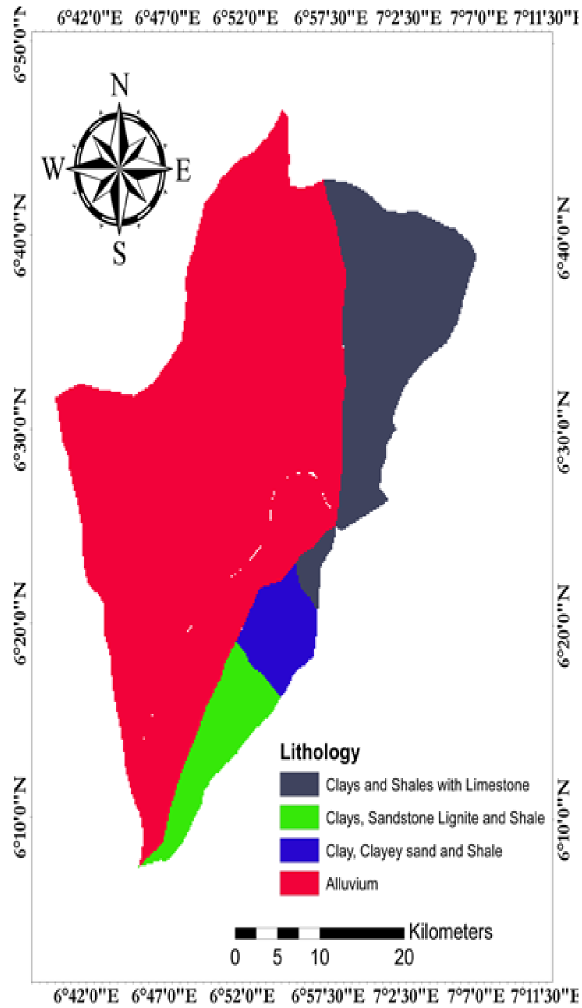

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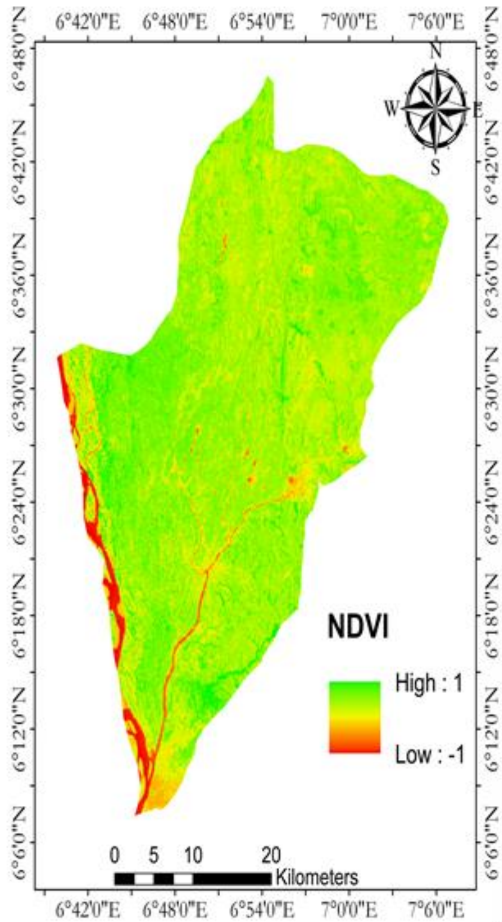

(i)

Figure 3: Flood conditioning factors (a) Slope, (b) Elevation (c) Aspect (d) SPI (e) LULC (f) Drainage density (g) Rainfall (h) Lithology (i) NDVI

5.2 Elevation and Aspect:

The dataset used for the elevation and aspect were calculated using the DEM. Floods tend to be identified in lower elevations due to the accumulation of water or rainfall downhill than on higher elevations due to gravitational force towards lower elevations (Cluster, 2020). Aspects aid to elevate the stability of slope on a terrain. These parameters are represented in figure 3b and 3c. Figure 3b shows that areas on red and yellow colouration, depicts flood prone areas; which include most parts of Anambra West, Anyamelum and very few areas of Anambra East.

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Figure 3c explains that areas on red and yellow colouration are susceptible to flood and this includes parts of Anambra West, Anyamelum and Anambra East; which make up Northern Anambra State. Green coloured areas are table land and some partly green areas are the anticipated non susceptible flood areas which include Nkwelle Nkwelle, Ukwu Abwa, parts of Umuleri Nando, Nsugbe, parts high grounds of Aguleri.

5.3 Stream Power Index (SPI):

SPI is another hydrological parameter influencing floods. It measures the erosive power of flowing water. Areas on blue, green and yellow coloration has low to moderate SPI, indicating vulnerability to flooding while areas on red are non-floodable/non susceptible to flood. SPI in this study was computed using equation (1)

$$SPI = A_S \text{ x } \tan\beta. \qquad (1)$$

Where A_S = Upstream drainage area

B = Gradient of slope in radius

5.4 Land Use Land Cover (LULC):

When considering factors that contribute to flooding, LULC is one of the important factors. The intensity and magnitude of a flood in an area can be determined by the LULC of the geographic location. In Fig. 3e red colouration represents developed areas. It is known that infiltration rate, runoff process, the evaporation rate of an environment such as in built-up areas, and deforestation or vegetation density can immensely influence flooding, as well as the level of flood. These areas with high LULC are prone to flooding due to poor permeability; thus, having a low infiltration rate. Areas on green colouration (Agricultural land and Vegetation) tend to experience a high flood because of the negative correlation between vegetation density and flooding. Blue coloured areas (Water bodies) makes those living around water bodies likely perceived to flood risk. The LULC of this study was generated from Landsat OLI and supervised classification of LULC was carried out in Figure 3e

5.5 Drainage Density:

Drainage density shows the amount of water in a watershed. It is the channel length of a unit in a water shed. Figure 3f red- and orange-coloured areas shows high drainage density, which indicate a high overland flow, indicating less infiltration thus higher flood risk and a high bifurcation ratio. Moderate drainage density is indicated by yellow and lemon colouration while green colour depicts low drainage density. The drainage density for this study (Figure 7) was derived using the formula:

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Dd = LT / Abasin (2)

Where Dd= Drainage density (km/km²)

LT = Total stream length of all orders

Abasin = Area of basin

5.6 Rainfall

When assessing flood conditioning factors, rainfall is the most important parameter. When high rainfall occurs, and the amount of water flow contained in the catchment area overpowers its drain capacity, this subsequently results in flooding. Thus, rainfall among other parameters is a major contributor to flooding. The rainfall map (Figure 3g) in this study was obtained by collections of rainfall data and was interpolated using the coordinates of the study. Dark blue-coloured areas have high amount of rainfall, which include places like northern parts of Anyamelum and Anambra West which are more susceptible to flooding while light blue-coloured areas show places with lesser amount of rainfall with little or no flood susceptibility.

5.7 Normalised Difference Vegetation Index (NDVI):

Vegetations are used to checkmate flooding because of their capacity to resist flooding and the ability of their leaves to intercept rainfall. For example, a healthy forest can serve as a runoff control. However; green coloured areas have high flood susceptibility (Figure 3i), yellow-coloured areas have moderate flood susceptibility while red coloured areas have low flood susceptibility. NDVI is one of the parameters which can be used for evaluating flood susceptibility. Hence, The NDVI in this study was produced using Sentinel 2 data acquired through a satellite sensor, using the equation:

$$NDVI = \frac{(NIR-R)}{(NIR+R} \qquad (3)$$

Where NIR is Near Infra-Red, this is the light reflected in the near infrared spectrum, R is the light reflected in the red range of spectrum

5.8 Lithology:

This involves the physical characteristics of the rocks such as their composition, colour, or texture. The susceptibility of a flood occurring in a location is also dependent on the permeability of the lithology of the area. For example, if a location is composed of impermeable rocks, it lowers the infiltration rate at which water is absorbed underground thus, increasing the flood risk. Alluvium (alluvial deposit due to erosion by rainwater) are usually characterized with the consequences of water overflow from streams, spreading to adjacent areas; here, alluvial areas are depicted with red colouration. Orange and lemon coloured areas shows clayed, shales and limestone areas, which has high compaction that Inhibits infiltration; which encourage flooding through high runoff. Green coloured areas are of clays, sandstone, lignite and shale, encourage flooding except sandstone areas (Figure 3h).

6. Modelling of flood Susceptibility

6. 1Modelling with Analytical Hierarchical Process (AHP)

AHP is a hierarchy structure which is used to develop priorities for alternatives by the user's judgement to resolve or represent a problem (Satty, 1980). It is mostly applicable when decision-making is complex.

6.2 Algorithms of AHP

The principle of AHP algorithms follows a matrix. AHP creates a computation of various criteria which is based on a pairwise comparison matrix (PCM). However, for a consistent pairwise comparison, transitivity and reciprocity rules must be respected (Ishizaka and Kasti, 2006). The derivation of the pairwise comparison matrix is given by

$$\mathrm{aij} = \mathrm{aij} \, . \, \mathrm{aji} \qquad (4)$$

$$\mathrm{aij} = \frac{1}{\mathrm{aji}} (5)$$

Where a_{ij} = Scale of the importance of one criterion relative to the other i, j and any of the matrix alternatives

i and j = Criterion relative to the other

Thus, if the criteria have the same importance (equation 5) or a criterion is measured to itself (equation 6) then

$$\mathrm{aij}.\,\mathrm{aij} = 1 \qquad (6)$$

$$\mathrm{ajj} = 1 \qquad (7)$$

Where jj is for every j factor

The pairing of a criterion is scaled from 1 to 9 (Table 1) or a reciprocal of the value. The Pairwise Comparison Matrix (PCM) is then calculated by aggregating each column and the normalized pairwise matrix (PM) was derived by averaging all the criteria in the row. Then the Consistency Ratio (CR) defines the validation (Equation 7) which must be < 0.1, however, a higher CR > 0.1 indicates an inconsistency of the judgement matrix thus, the weight must be re-estimated.

$$\mathrm{CR} = \frac{CI}{RI} \qquad (8)$$

Where CR = Consistency Ratio

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CI = Consistency Index
RI = Random Index

$$CI = \frac{\lambda max - n}{n-1} \quad (9)$$

where n = Number of matrix

RI (Random Index) (Table 2) is the consistency index. It adopts the consistency of the comparison matrix attained by the decision maker (Shyamprasad and Kousalya, 2020).

Table 1. Judgement Scale

Value (a_{ij})	Description	Explanation
1	i and j are equally important	i and j factors contribute equally
3	i is slightly moderately important than j	Judgement moderately favours i over j
5	i is of strong importance than j	Judgement favours i over j
7	i is of very strong important than j	Judgement strongly favours i over j and its dominance is evident in practice
9	i is extremely important than j	Judgement used when it is evident i is prevalence over j
2,4,6,8	i and j are of intermediate values	Judgement is used when i and j are intermediary
1/3, 1/5, 1/7, 1/9	Values for inverse comparison	Judgement is used when i is reciprocated by j

Table 2. Value of Random Index for fewer problems

n	1	2	3	4	5	6	7	8	9
R	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.49

The AHP applied was based on relative importance by comparing the value of each row with each column. Ranking of relative importance is based on the decision of the decision maker; however, the CI must be < 0.1 after the judgmental decision. The parameters for the flood susceptibility map were ranked based on

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the pairwise comparison matrix, subsequently, the criteria weight (CW) was calculated based on the Normalised pairwise comparison matrix. The calculated the eigenvalue (λmax), CR and CI of 9.508, 0.063 and 0.043 respectively were used to compute and produce the flood susceptibility map. Based on the CR being < 0.1, AHP analysis was modelled in GIS with rainfall, slope, aspect, lithology, LULC, elevation, SPI, NDVI, and drainage density, having a CW of 24%, 17%, 13%, 11%, 9%, 8%, 7%, 6%, and 5% respectively.

6.3. Algorithms of LBWM

The LBWM uses alternatives to evaluate the criteria in order to select the best alternative(s). BWM, the best (most important) and the worst (least important) are identified by the decision maker. It determines the decision criteria of each criterion which is based on the most important and least important criteria and pairwise comparisons are then conducted between most important and least important with the other criteria (Rezaei, 2015). The steps for determination of weight on BWM are:

Step 1: The determination of the set of the decision criteria
Step 2: Determination of the best and worst criteria with other least criteria and their preference quantifying them using a scale
Step 3: Determination of weight using linear programming model below:

$$\text{Min } \xi_{1=} \begin{cases} \left| w_{b-a_{B_j} w_j} \right| \leq \xi_t \quad for\ all\ j \\ |w_b - ajw\ w_w| \leq \xi_t\ for\ all\ j \\ \Sigma_{w_J:=1} \\ w_j \geq 0\ for\ all\ j \end{cases} \tag{10}$$

Where $\xi_{L\,=}$ Constraints, $W_{b\,=}$ Weight for the best criteria, a_{bj}= Coefficient of the criteria and W_j = the weight of a individual criteria to be weighted, a_{jw} =Coefficient of a criteria, W_w= weight of the worst criteria. The $\sum_{wj}$=1 implies that the overall weight of the criteria must be equal to 1 when summed up and the Wj $\geq$ 0 implies that the weight of a particular criteria must be greater than or equal to zero and j represents all the criteria.

Step 4: Solving the linear programming model

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$$\begin{vmatrix} Wp - 8W_R \\ Wp - 6W_s \\ Wp - 4W_A \\ Wp - 5W_{dem} \\ Wp - 4W_{DD} \\ Wp - 2W_{lith} \\ Wp - 1W_{spi} \\ Wp - 5W_{lulc} \\ Wp - 5W_{ndvi} \end{vmatrix} \begin{matrix} \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \\ \geq \xi_L \end{matrix} \quad (11)$$

We obtained the following ranking for the criteria with a Ksi of 0.07 on table 3. In BWM, a Ksi value close to zero signifies a superior consistency and a Ksi close to 1 indicates inferior consistency. We approximated the decimal numbers to whole for seamless running of algorithm by GIS.

Table 3. Criteria weights of BWM with Ksi

Weight	**Rainfall (W_R)**	**Slope (W_S)**	**Aspect (W_A)**	**DEM(W_{dem})**	**DD (W_{DD})**	**Lithology (W_{lith})**	**SPI(W_{spi})**	**LULUC(W_{lulc})**	**NDVI(W_{ndvi})**
Ksi*=0.07930	0.3405	0.139	0.1049	0.0839	0.0699	0.05998	0.0326	0.0839	0.0839

6.4 Algorithm of CRITIC method

The index accumulated weight of critic method can be based on objective information (Liu and Zhao,2013). We employed the objective approach in the solving for the critic method. The most flood influencing factor was regarded as the best criteria and the least flood influencing factor as the worst criteria.

Step 1: Formulation of the decision matrix

We formulated the decision matrix between the criteria. We applied objective method for decision matrix.

Step 2: Normalisation of the input matrix

$$\bar{x}_{ij} = \frac{x_{ij} - x^{\text{worst}}}{x_j^{\text{best}} - x^{\text{worst}}} \quad (12)$$

Where $\bar{x}_{ij}$is the mean of the normalised value of alternative i with respect to criterion j, xij is the actual score of alternative i with respect to criterion j, $xjbest$ is the best score (most important value) of criterion j, and $xjworst$is the worst score (least important value) of criterion j.

Step 4 Estimating the standard deviation (SD) of the normalised matrix

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After employing equation 13 below to estimate the SD, we determined the correlation where α_j is the SD, $\bar{xj}$ is the mean value of criterion j and n is the total number of alternatives We calculated the SD of the normalised matrix (equation 12) using the formula below:

$$a_j = \sqrt{\frac{\left(\sum_{L=1}^{n} x_{ji} - \overline{x_j}\right)^2}{n-1}} \tag{13}$$

Step 5: Determination of the correlation of the criteria.

We determined symmetric matrix (which is the linear correlation of the criteria equation 14) after employing equation 13 to estimate the SD of the criteria. This symmetric matrix models the relationships between the criteria. This is done to eliminate possible conflict in the weightage among the criteria.

$$\sum_{k=1}^{n}(1 - r_{jk}) \tag{14}$$

Where rjk is the linear correlation coefficient between vectors x_j and x_k, n is the sample size of a criterion

Step 5: Determine the information of the criteria

$$c_j = \alpha_j \cdot \sum_{k=1}^{n}(1 - r_j k) \tag{15}$$

Where cj is the criterion information quantity

Step 6: Determination of the objective weight

We then determined the objective weight of the matrix applying equation 16 below. This step measures the conflict created by the criterion and then derive the objective weight of the criterion. Thus, the objective weight was used to estimate the weight of the criteria

$$\omega_j = \frac{c_j}{\sum_{k=1}^{n} c_j} \tag{16}$$

Where ω_j is the criterion weight, c_j is the criteria information quantity

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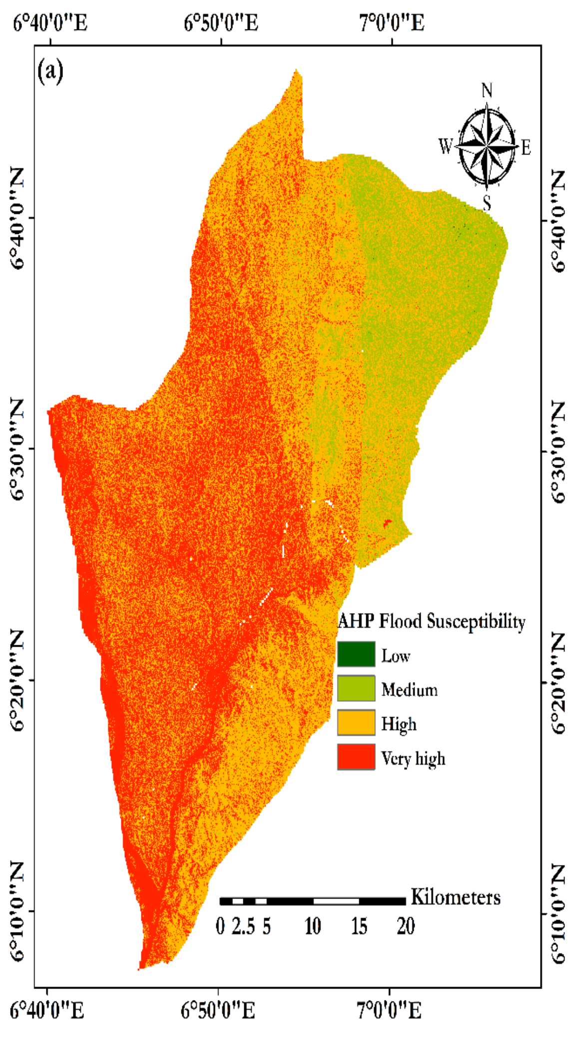
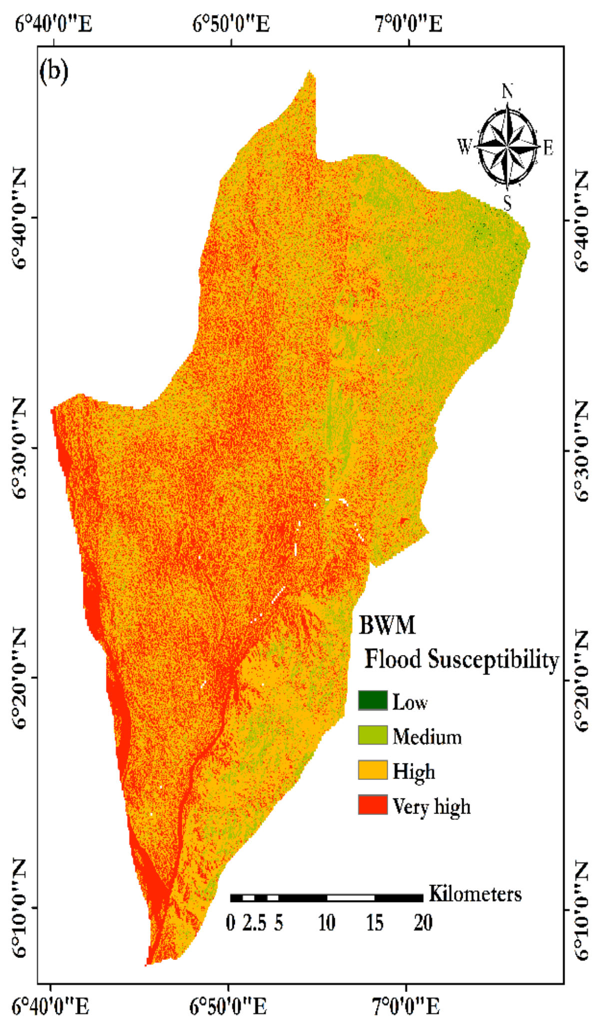
Table 4. Criteria weights derived by Critic method

	Rainfall	Slope	Aspect	DEM	DD	Lithology	SPI	LULUC	NDVI
Weight	10.88	10.74	25.06	7.53	8.66	12.26	9.39	8.87	6.61



(a)



(b)

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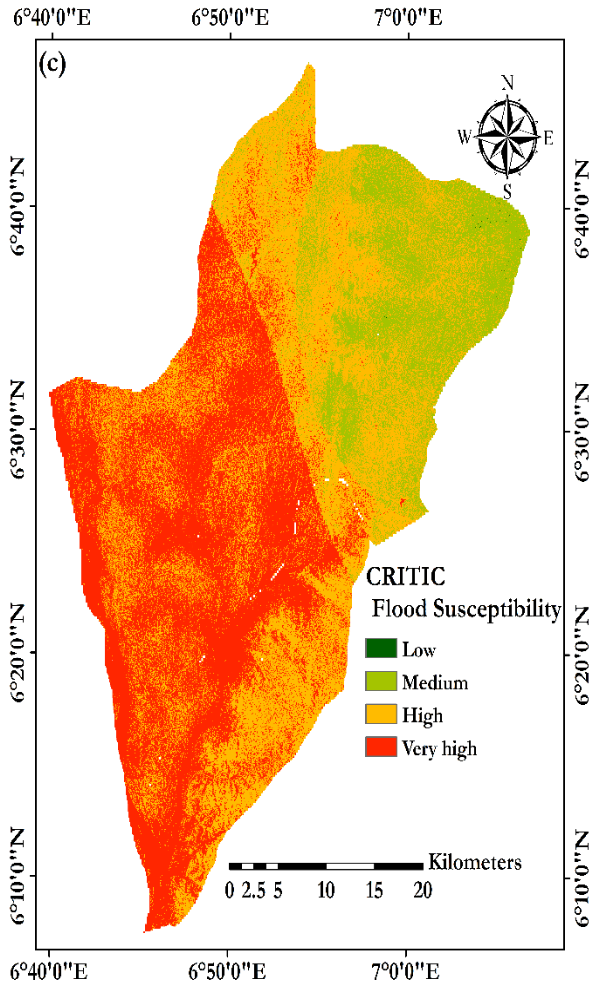

(c)

Figure 4: Flood Susceptibility factor (a) AHP Flood Susceptibility (b) BWM Flood Susceptibility (c) CRITIC Flood Susceptibility

7. Flood Susceptibility map algorithm

The flood susceptibility map of each MCDM was derived by multiplying the values from individual weighted criteria and scoring each of the conditioning factors by aggregating the values using the equation below

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$$FSI = \sum_{i-1}^{n} w_i x_i \qquad (17)$$

Where FSI is Flood susceptibility index, w_i is weight of each criterion and x_i is the score of each conditioning factor.

8. Flood Inventory

To achieve flood susceptibility mapping, the flood inventory, which indicates the inundated zones are essential. The inventory mapping can determine the accuracy of the flood susceptibility mapping. It can be used to evaluate the significance of the AHP, BWM and CRITIC susceptibility map. This study, identified 87 flood location points based on the State Emergency Management Agency report, field survey and historical reports. Flood Inventory is based on the accessibility of inventory data, and there is no precise rule or pattern for modelling flood inventory. The flood inventory report was integrated with the flood susceptibility map to validate the flood susceptibility produced (figure 4)

9. AHP, BWM and CRITIC method Flood Susceptibility Validation

Area Under Curve (AUC) is widely used by researchers to verify the accuracy of their models (Vojteket al, 2021; Ha et al, 2021). We employed the *Receiver Operating Characteristic (*ROC) curve to validate the accuracy of our model. The ROC curve plots true positive rate (TPR) on the x-axis and false positive rate (FPR) on the y-axis using different threshold values, which correspond to sensitivity and specificity value. The flood dataset was spliced into the testing and training datasets. We use 20% for testing and 80% for training; testing dataset were used to evaluate the model fit. The validation process was employed by evaluating the flood points by the AHP, BWM and CRITIC flood susceptibility mapping. The validation of the Area Under Curve (AUC) shows the accuracy of the AHP, BWM and CRITIC model was 0.735 or 74%, 0.728 or 73% and 0.775 or 78% respectively (Figure 5) at a 95% confidence interval which indicates good accuracy and an acceptable index of accuracy.

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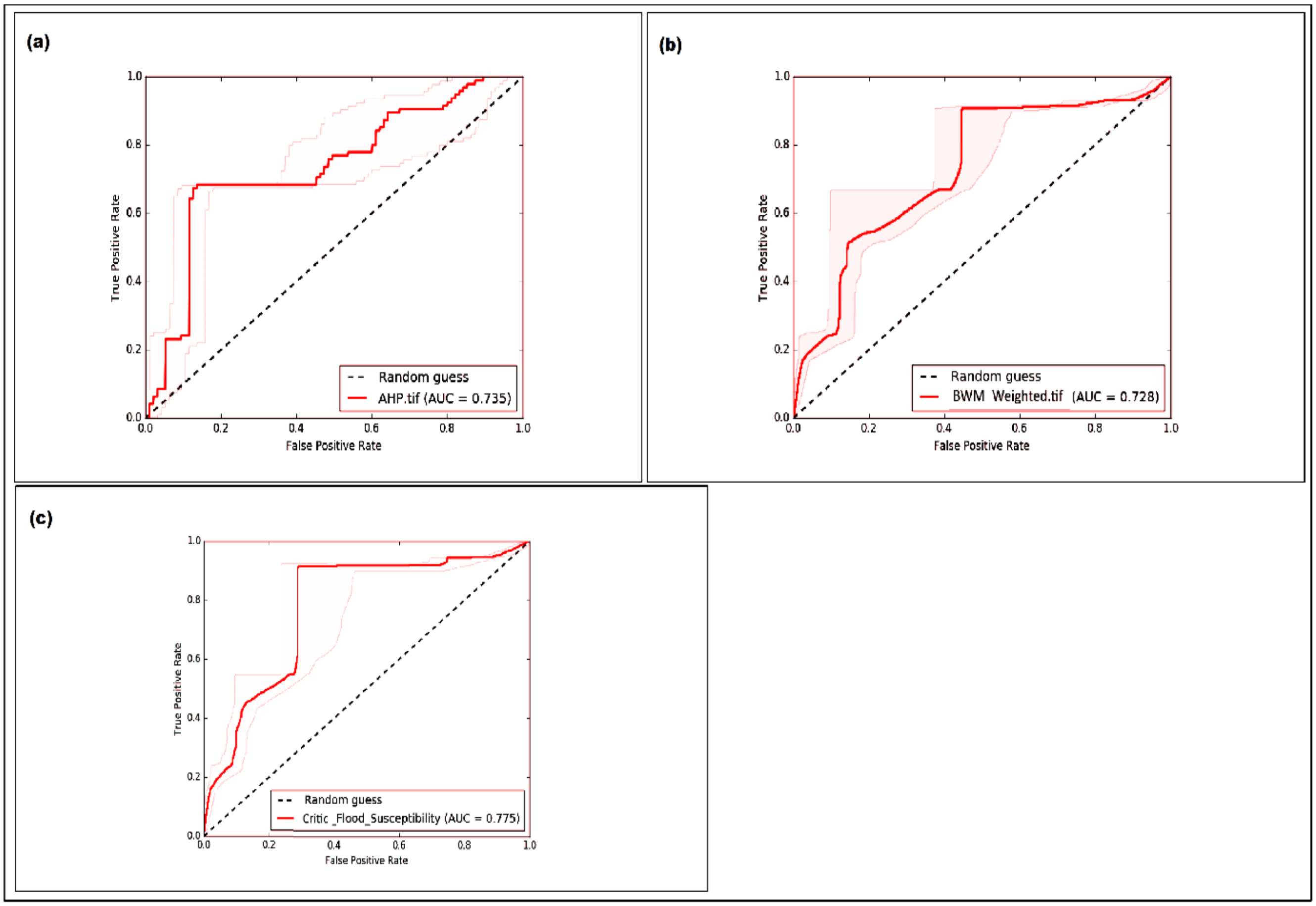

Figure 5. ROC curve and AUC flood susceptibility model graph (a)AHP graph model (b) BWM graph model (c) Critic graph model

10. Discussion of Result

Flood susceptibility map was created by employing the AHP, BWM and CRITIC technique (Figure 12). However, the GIS AHP, BWM and CRITIC flood susceptibility map (Figure 4) was classified into four classes, low, moderate, high and very high susceptibility. Analysis of the data of AHP showed that over 89.2% is high and highly susceptible to flooding. This indicates that about 89% (from flood susceptibility classes) of the land area is prone to flooding. BWM model show that approximately 87. 8% is high and highly susceptible to flooding. This indicates that about 88% (from flood susceptibility classes) of the land area is prone to flooding. The CRITIC method showed that 86% is, high and highly susceptible to flooding. Thus, indicating that about 86% (from flood susceptibility classes) of the land area is equally prone to flooding. In this study, the rainfall is weighted as the highest influencing factor by AHP and BWM, except

CRITIC weighing aspect as a higher conditioning factor over others. With the high AUC of 77.5% approximately 78% from the CRITIC method, shows that the method predicted the areas susceptible to flood more than the AHP and BWM method.

11. CONCLUSION

In our research, we employed nine conditioning flood parameters to model flood vulnerability zones using three multicriteria decision making. There has been little research on flood vulnerability zones in Northern Anambra state which as a result, lead to loss of lives and property at any flood incidence within the zone. This work is a guide in establishing vulnerability zones within the local government. After modelling the susceptibility zones, we performed a cross validation on our modelled result. The AUC affirmed the effectiveness and accuracy in our model. Our model has proven its reliability on predicting and mapping vulnerability zones. Thus, it can be utilised by agencies and organisations to identify vulnerability zones in the region for proper disaster management.

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