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GIS-Based Flood Vulnerability Assessment Using Integral Value of Inverse Function Ranked Fuzzy-AHP Technique.

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Abstract— Flooding is a common natural disaster which often causes extensive agricultural, infrastructural and socio-economic damages. In this study, a Geographic Information System (GIS) based flood vulnerability assessment using an improved integral value of inverse function ranked, Fuzzy Analytical Hierarchical Process (FAHP) technique for fast and accurate computation of flood vulnerability assessment across Oyo State, Southwest Nigeria is presented. The flood vulnerability assessment focuses on determining the spatial extent and flood vulnerability class of cultivated lands, settlements and road infrastructures across the study area for effective flood management. Based on the literature review, six prominent flood causative factors namely, elevation, slope, soil, rainfall, drainage density and land use/land cover were used as input criteria in this study. The improved integral value ranked FAHP technique uses both the left and right inverse function of a triangular membership function with an index of optimistic function to derive the weight for each input criterion. A flood vulnerability map for the study area was created using Geographic Information System (GIS) techniques based on the aggregation of the input causative criteria and their derived weights. Furthermore, maps showing the spatial extent and the flood vulnerability classes of cultivated lands, settlements and paved road infrastructures across the study area were made. The output vulnerability maps serve as an early warning system that would further assist policymakers and stakeholders in minimizing the effects of flooding on food security, road infrastructures, lives and properties across the study area.

Keywords/Index Terms—Fuzzy AHP, Geographic Information System, Food security, Road Infrastructure, Flood vulnerability.

1. Introduction

Flooding is a commonly occurring natural disaster, which often leads to extensive agricultural, infrastructural and socio-economic damages. It is one of the key global challenges of the twenty-first century, with future flood risk being exacerbated by climate change and rapid urbanization which negatively impact agricultural lands, food security, road infrastructures, human lives and properties (He et al. 2022, Yildirim and Demir 2022, Oskorouchi and Sousa-Poza 2021, Donnell and Thorne 2020, Kandari et al 2022). Between 2008 and 2018, flooding was ranked as the second driving factor that led to livestock and crop production losses globally (FAO, 2021). In Nigeria, flooding has also been identified as a major impediment to agriculture and food security (Week and Wizer 2020; Areola 2020). In 2020, close to 79 per cent of farmers in Nigeria were affected by the devastating effects of drought and flooding (premiumtimesng.com 2020). Flooding also causes extensive damage to road infrastructures which can lead to human death, damage to vehicles and grave economic losses (He et al., 2022; Singh et al., 2018; Ighile et al., 2022). Thus, the assessment of flood exposure and vulnerability of road infrastructure, agricultural lands and human settlements are crucial for sustainable flood risk management and the socio-economic well-being of our society (Kandari et al., 2022; Papilloud et al., 2020; Areola 2020).

Oyo state, located in Southwest Nigeria has a history of devastating floods which had negatively impacted lives and properties alongside causing damages to road infrastructures and significantly disrupting agricultural production in the state (Ajibade et al., 2021, Eguaroje et al., 2015). The August 2011 flood in Ibadan, the capital city of Oyo state (largest indigenous city in Nigeria) readily comes to mind. Furthermore, Oyo state is a major food basket in the Southwest region of Nigeria. This makes the search for more effective flood mitigation and management strategies of utmost importance (Olowe 2021; Obeta 2014).

Accurate flood vulnerability assessments are

important for effective flood mitigation and management strategies (Atijosan et al., 2021; Liu et al., 2021; Nasiri et al., 2018; Gigović et al., 2017) as information from the flood vulnerability assessments will better aid preparedness, and planning by all stakeholders (Ali et al 2019). The decision-making process is critical in flood vulnerability assessment, as it impacts the effectiveness of the flood management measures taken to reduce the consequences of flooding. Thus, computational intelligence that can make accurate and timely decisions is highly needed (Olowe 2021).

Flood vulnerability assessment is a complex and multidimensional problem that needs to take into account various criteria needed for its assessment. Multi-criteria Decision Making (MCDM) tools are powerful tools for suggesting solutions for problems where there are many decision criteria (Milošević, et al., 2020). The fuzzy Analytic Hierarchy Process (FAHP), an intelligent computational tool, has evolved to be a popular and effective MCDM problem-solving technique due to its practical application and ability to handle ambiguous data and uncertainties (Milošević, et al., 2020; Tahri et al., 2017). Various FAHP techniques exist in the literature for ranking and deriving weights to the available criteria. Popular among these techniques are the fuzzy extent analysis method (Chang 1996; Ahmed and Kilic 2015) and the integral value method (Liou and Wang, 1992; Yu and Dat, 2014). The integral values method as proposed by Liou and Wang 1992 and modified by Vincent and Dat 2014, is a commonly used approach with wide applications (Sam'an et al 2020; Vincent and Dat 2014). Compared to the fuzzy extent analysis method, it is efficient in ranking fuzzy numbers as it can represent the relative importance of two or more triangular fuzzy networks (TFNs) rather than just an index signifying the degree of the greatness of one TFN compared to others (Ruan et al 2015; Kabir and Sumi 2014; Kabir and Hasin 2012), thus improving accuracy. Nonetheless, there are shortcomings with the integral value method that bothers on limitations and inconsistency (Sam'an et al., 2020; Vincent and Dat 2014). To enhance the accuracy of flood vulnerability assessments an improved integral

value method that uses the left and right inverse function of a triangular membership function with an index of optimism is used for flood vulnerability assessment in this study. To the best of our knowledge, this method has not previously been applied in the literature to assess flood vulnerability. Furthermore, a single fuzzy-AHP pairwise comparison matrix was developed for ease and fast computation of flood vulnerability assessment. In this study, emphasis was placed on identifying the vulnerability class and spatial extent of flood vulnerability of settlements, cultivated lands and paved road infrastructures across the study area, Oyo state, South-west Nigeria. Early warning information from the flood vulnerability assessment can potentially assist decision-makers, farmers and the general populace in preparing for probable flooding and help minimize the risk of flood disasters to food security, road infrastructures, lives and properties in Oyo State. The rest of the paper is organized as follows. Section 2 “Related works” highlights reviewed literatures and contributions. Section 3 “Methodology” presents the developed method. Furthermore, section 3 describes the assessment and mapping of flood vulnerability within the study area using GIS tools. Section 4 “Results and discussion” details the results obtained from the flood vulnerability assessment and discusses its potential implications on croplands, human settlements and infrastructure within the study area. Conclusions are given in the “Conclusion” section and directions for future research are highlighted.

Table 1: Summary of related works.

2. Related work

Table 1 highlights a review of related works. Major contribution of this work are

- An improved fuzzy-AHP integral value method for flood vulnerability assessment.
- Use of a single fuzzy-AHP pairwise comparison matrix for fast and easy computation of flood vulnerability.

3. Methodology

Materials and methods used for assessing flood vulnerability in the study area are presented here.

3.1 Study area

The study area is Oyo State, located in the south-western region of Nigeria. Oyo state covers a total of approximately 28,000 square kilometres with an estimated population of approximately 5.5 million inhabitants (Daramola et al., 2022, Adeyemi 2021). The state lies within the tropical climatic region with two distinct seasons, dry and wet seasons (Oyewole et al., 2017). Oyo State has an estimated agricultural landmass of 27,000 sq km and a favourable climate for equatorial crop production and livestock rearing. Agriculture is currently the major contributor to Oyo State’s economy, comprising 38% of gross state product (GSP) and directly or indirectly employing as much as 70% of the workforce (oxfordbusinessgroup.com). Oyo state has a history of ravaging flood disasters which have adversely affected the lives and properties of residents, damaged road infrastructures and disrupted agricultural production (Ajibade et al., 2021, Eguaroje et al., 2015).

Research works	Methodology	Strength	Weakness
Selvam and Jebamalai 2023; Nsangou et al., 2022; Ouma, Y.O. and Tateishi, R. (2014).	AHP	Simple and effective method for modelling unstructured problems.	Inability of AHP techniques to effectively estimate uncertainty and vagueness in the decision making process
Afsari et al., 2022; Ekmekcioğlu et al., 2021	FuzzyAHP (fuzzy extent analysis method)	ability to better handle ambiguous data and uncertainties than AHP	Less effective in ranking fuzzy numbers (Ruan et al 2015; Kabir and Sumi 2014)
Atijosan et al., 2021 Sam’an et al., 2020	FuzzyAHP (integral value method)	More efficient in ranking fuzzy numbers compared with fuzzy extent analysis method	Still has some limitations and inconsistencies that reduces accuracy. (Sam’an et al., 2020)

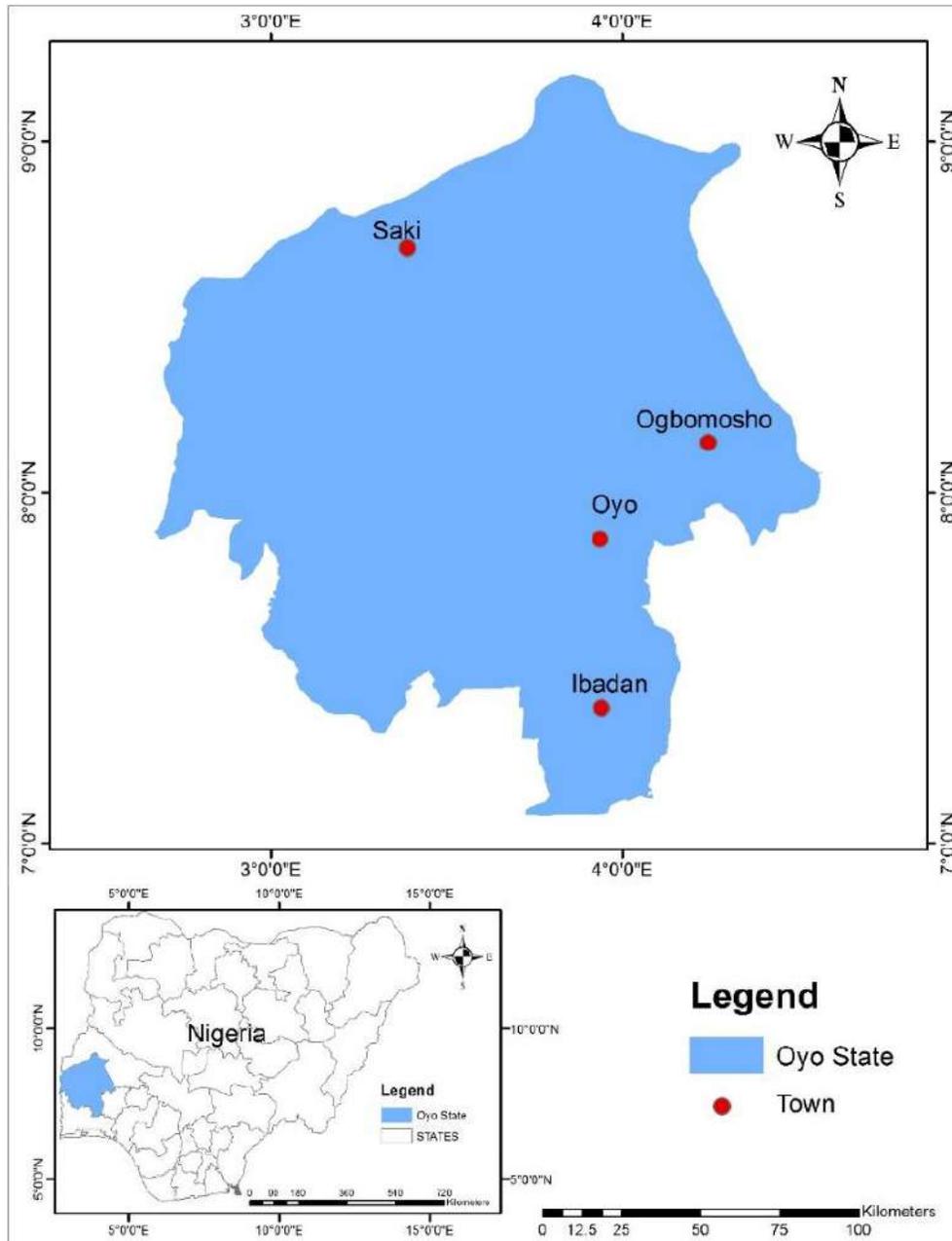


Fig. 1: Study area map

3.2 Selection of Factors for Flood Vulnerability Analysis

Input factors used were elevation, slope, soil, rainfall, land use/land cover and drainage

density. Choice of criteria were identified from within relevant literature and experts' opinions. The datasets used in the study are highlighted in Table 2.

Table 2: Datasets used in the study

No	Datasets	Description	Source
1	Digital Elevation model (DEM)	ASTER data (resolution of 30m)	USGS earth explorer
2	Slope	Derived from DEM (resolution of 30m)	DEM
3	River line	River course across Nigeria	Humdata (data.humdata.org)
4	Drainage density	Extracted from Drainage network	Drainage network (data.humdata.org)
5	Rainfall	Downscaled IPCC5 (CMIP5) data using GSM CCSM4 Under scenario RCP 6.	WorldClim-Global Climate data http://www.worldclim.com
6	Soil	1996 compilation of soil map for Nigeria: A nationwide soil resource and land form inventory (Resolution 1:300000)	Centre for World Food Studies
7	LULC	ESRI 2021 Global LULC (resolution of 10m)	ESRI 2021 Global LULC
8	Road	Extracted roads from OpenStreetMap data by WFP	WFPGeoNode

3.3 Flood inducing factors

3.3.1 Drainage density

Drainage density is an important influencing factor for flood hazard because an increasing drainage density implies increasing flood peaks (Pallard et al., 2009). Drainage density was extracted from the drainage network across the study area and calculated as $D = L / A$, where D is drainage density across the study area, L is the total length of the drainage channel in the study area and A represents the total area. The original and reclassified drainage density maps are shown in Figures 2a and 2b.

3.3.2 Digital Elevation Model

Elevation is an important factor in flood vulnerability assessment (Chen et al., 2021). Digital elevation data used in this study was extracted from the advanced space-borne thermal emission and reflection radiometer (ASTER) global digital elevation model (DEM) with a resolution of 30 m. The original and reclassified elevation maps are shown in Figures 3a and 3b.

3.3.3 Rainfall

Rainfall is a major factor in the occurrence of flooding (Echendu 2022). Predicted precipitation data was used in this study. The original and reclassified rainfall maps are shown in Figures 4a and 4b.

3.3.4 Slope

The slope is also an important factor in assessing

flood vulnerability as it is crucial in determining surface run-off velocity and vertical percolation (Rahmati et al 2015). A slope map was obtained from the DEM. The original and reclassified slope maps are shown in Figures 5a and 5b.

3.3.5 Soil

Soil composition is also a factor for flooding as the soil infiltration capacity determines the ability of the soil to absorb water, thus, reducing or decreasing run-off (Ighile et al., 2022; Ouma and Tateishi 2014). Soil map was obtained from a 1996 compilation of soil maps for Nigeria by the Centre for World Food Studies (SOW-VU). It has a resolution of 1:300,000. The original and reclassified soil maps are shown in Figures 6a and 6b.

3.3.6 Landuse and Landcover (LU/LC)

Land use/land cover is a crucial factor for flood occurrence (Tudunwada and Abbas 2022; Alimi et al., 2022). LULC was obtained from ESRI 2021 Global LULC map with a resolution of 10m. Five classes were used namely, waterbody, agricultural land, vegetation, settlement and rock outcrop. The original and reclassified LULC maps are shown in Figures 7a and 7b.

3.4 Reclassification of Criteria

Each of the criteria source map (figures. 2a, 3a, 4a, 5a, 6a and 7a) were reclassified into five classes (very high, high, moderate, low and very low) as shown in figures 2b, 3b, 4b, 5b, 6b and 7b. Reclassification was done using the natural

breaks (Jenks) classification method. Jenks's classification method is based on natural groupings inherent in the data). Reclassification

was used to group ranges of values in each of the criteria source maps into single values among the five classes.

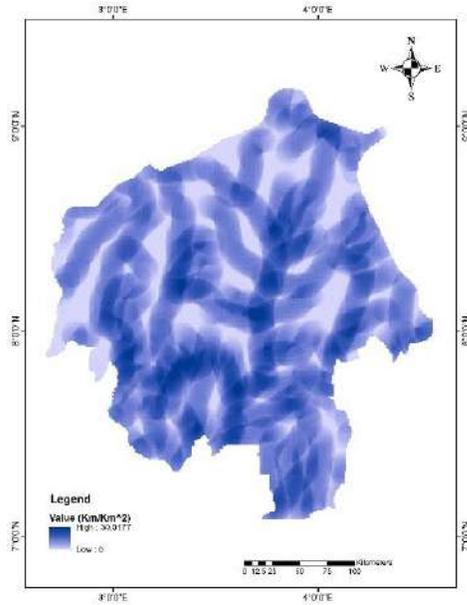
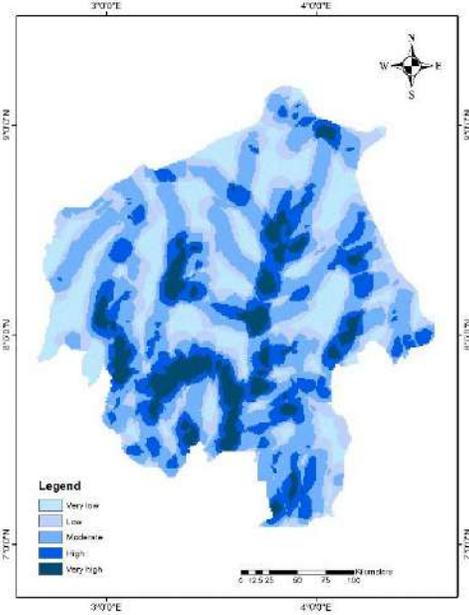


Figure 2: (a) Drainage density



(b) Reclassified Drainage density

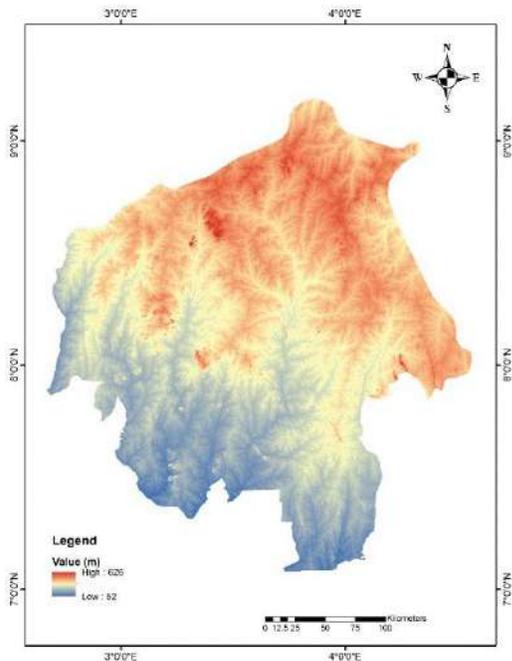
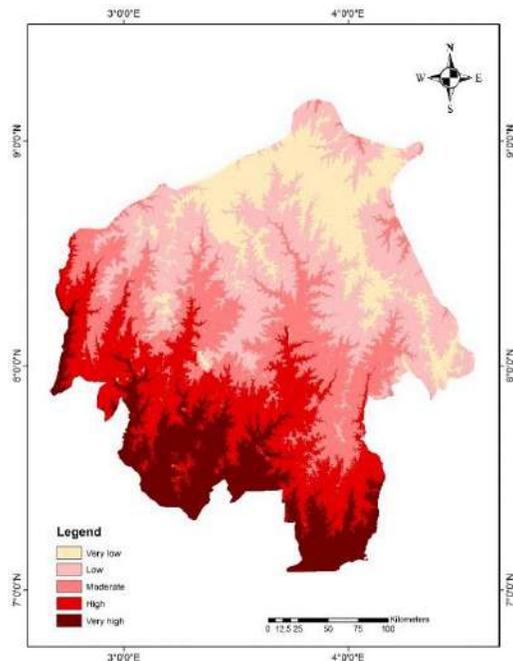


Figure 3: (a) Digital elevation model



(b) Reclassified Digital elevation model

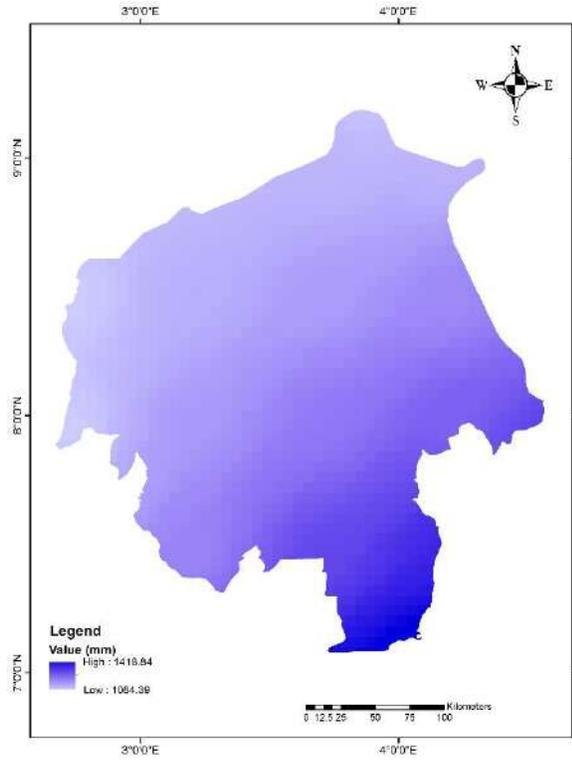
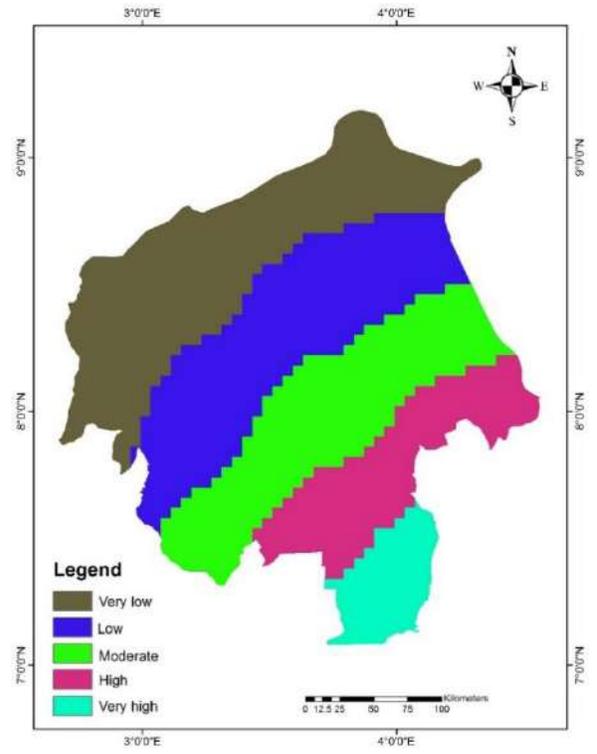
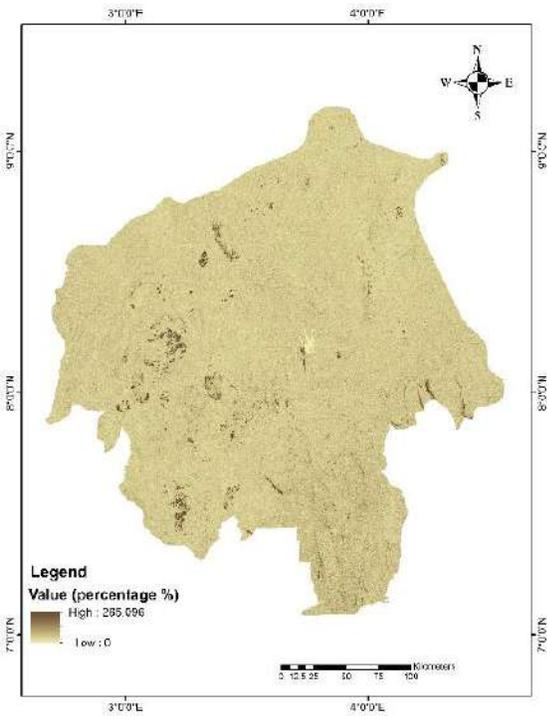


Figure 4: (a) Rainfall



(b) Reclassified Rainfall



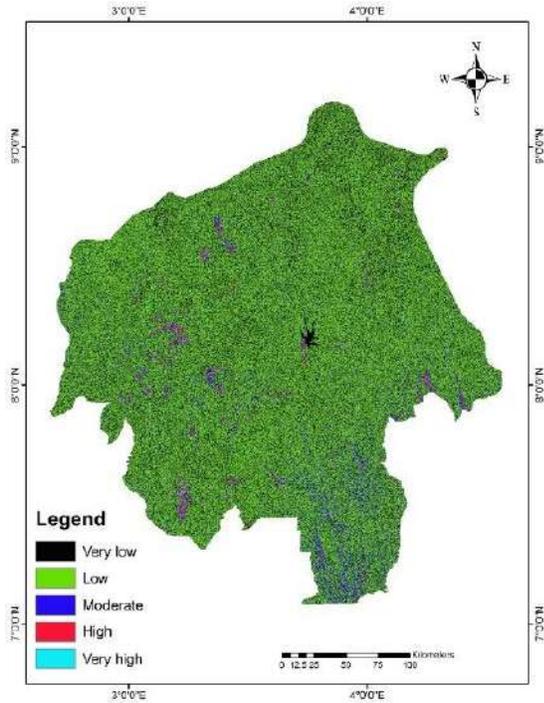
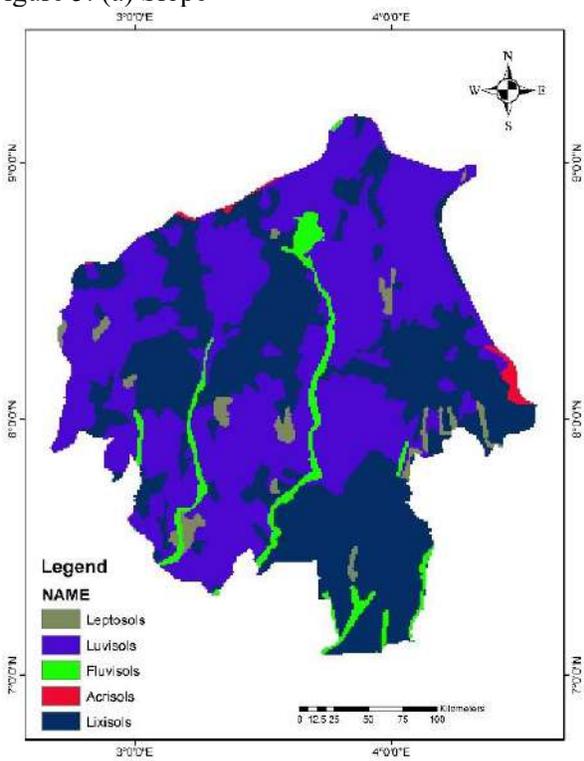


Figure 5: (a) Slope

(b) Reclassified Slope



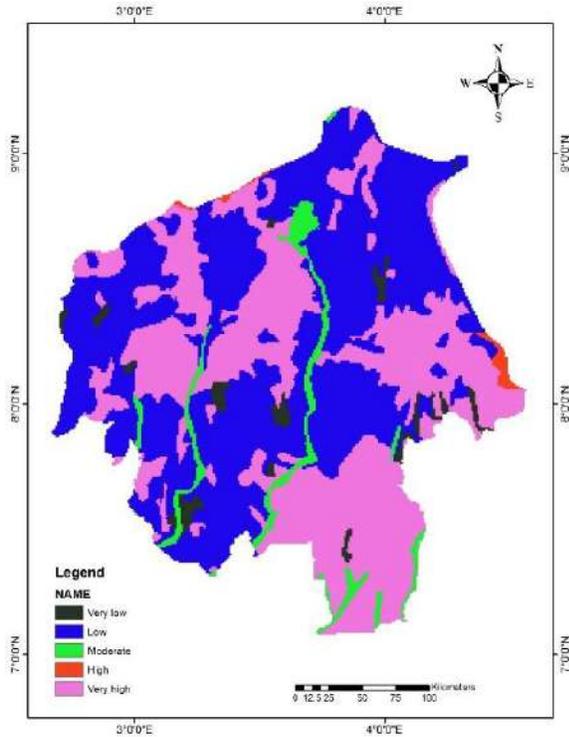


Figure 6: (a) Soil

(b) Reclassified Soil

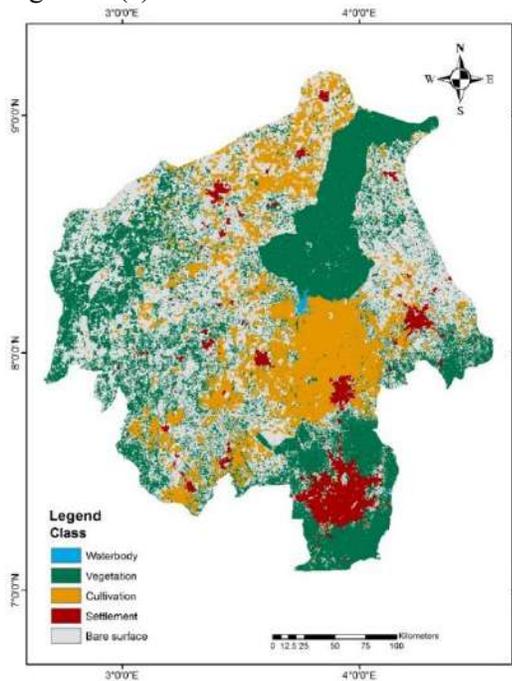
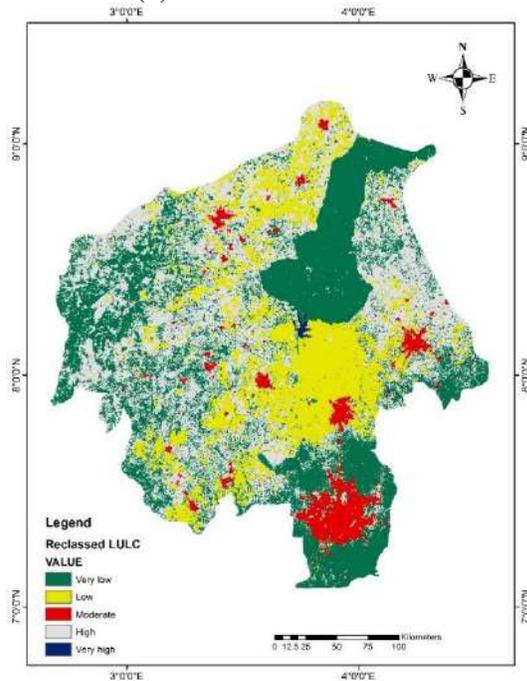


Figure 7: (a) LULC



(b) Reclassified LULC

3.5 Fuzzy Analytic Hierarchy Process (FAHP)

Fuzzy sets are effective mathematical tools for handling uncertainty in decision-making (Jun et

al 2013). A fuzzy number belongs to the closed interval 0 and 1, where 1 stands for full membership and 0 stands for non-membership. FAHP is an extension of fuzzy set theory where linguistic variables gotten from experts and decision makers while developing the pairwise

comparison matrix are represented using fuzzy numbers (Ahmed and Kilic 2015). Different types of fuzzy numbers exist (e.g trapezoidal fuzzy numbers as shown in Figure 8) but it is convenient to work with triangular fuzzy numbers due to ease of computation and usefulness in representing information in a fuzzy environment (Jun et al 2013). The membership function of each TFN can be described mathematically using equation 1 (Jun et al 2013) and TFNs can be represented graphically using figure 9. Table 3 shows the TFN scale, definition and linguistic variables used in this study.

$$\mu_{\tilde{N}}(x) = \begin{cases} 0 & x \leq l, \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where l denote the smallest possible value, m the most promising value and u the largest possible value that describes a fuzzy event.

Table 3. TFN scale, definition and linguistic variables

TFNs (l,m,u)	scale	Definition	Linguistic variables
(1.0,1.0, 1.0)		Just equal	Just equal
(1.0, 1.0, 3.0)		Equal importance	Least Importance
(1.0, 3.0, 5.0)		Moderate importance of one over another	Moderate Importance
(3.0, 5.0, 7.0)		Essential or strong importance	Essential Importance
(5.0, 7.0, 9.0)		Demonstrated importance	Demonstrate Importance
(7.0, 9.0, 9.0)		Extreme importance	Extreme Importance

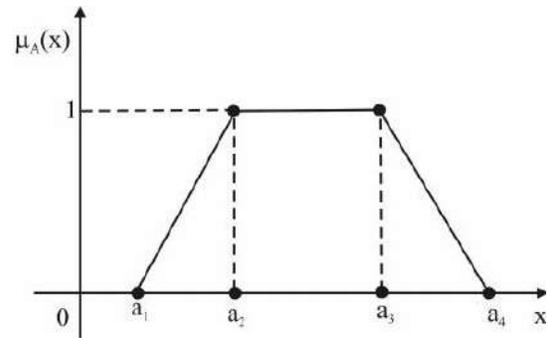


Figure 8: Trapezoidal fuzzy number

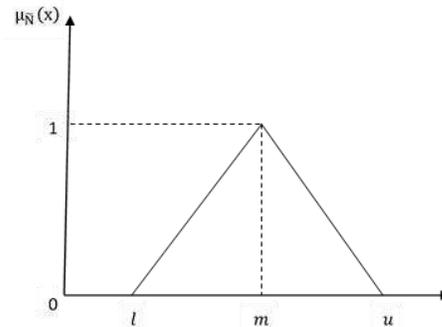


Figure 9: Triangular fuzzy number

3.5 Weights Determination

Weight determination was carried out using the steps outlined below;

- Develop the fuzzy AHP pairwise comparison matrix of criteria.
- Compute weights for each factor in the fuzzy AHP pairwise comparison matrix using the improved integral value of inverse function.

Sections 3.5.1, 3.5.2 and 3.5.3 details this steps. Fuzzy consistency ratio is detailed in section 3.5.4

3.5.1 Fuzzy-AHP pairwise comparison matrix

Develop a fuzzy-AHP pairwise comparison matrix of criteria such that:

$$\tilde{P} = \{\tilde{p}_{ij}\} = \begin{bmatrix} (1,1,1) & \tilde{p}_{12} & \cdots & \tilde{p}_{1n} \\ \tilde{p}_{21} & (1,1,1) & \cdots & \tilde{p}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{p}_{n1} & \tilde{p}_{n2} & \cdots & (1,1,1) \end{bmatrix} \quad (2)$$

where pairwise comparison judgments are represented by fuzzy triangular numbers $\tilde{p}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ for a pirorisation problem at a level with n elements.

Table 4 shows the pairwise fuzzy comparison

Table 4: Pairwise fuzzy comparison matrix of input factors using triangular fuzzy number scale

	LULC			Rainfall			DEM			Drainage density			Slope			Soil		
	l_i	m_i	u_i	l_i	m_i	u_i	l_i	m_i	u_i	l_i	m_i	u_i	l_i	m_i	u_i	l_i	m_i	u_i
LULC	1	1	1	1/7	1/5	1/3	1/3	1	1	1/5	1/3	1	1	1	3	1	3	5
Rainfall	3	5	7	1	1	1	1	3	5	1	1	3	5	7	9	7	9	9
DEM	1	1	3	1/5	1/3	1	1	1	1	1/3	1	1	1	3	5	3	5	7
Drainage Density	1	3	5	1/3	1	1	1	1	3	1	1	1	3	5	7	5	7	9
Slope	1/3	1	1	1/9	1/7	1/5	1/5	1/3	1	1/7	1/5	1/3	1	1	1	1	1	3
Soil	1/5	1/3	1	1/9	1/9	1/7	1/7	1/5	1/3	1/9	1/7	1/5	1/3	1	1	1	1	1

where parameters l_i , m_i , and u_i respectively denote the smallest value, most promising value and the largest possible value that describes a fuzzy event.

matrix developed using equation 2 and the triangular fuzzy numbers scale described in table 2. A single Fuzzy-AHP pairwise comparison matrix was developed for ease and fast computation of flood vulnerability assessment.

3.5.2 Compute weights for each input criteria from the pairwise comparison matrix using the improved integral value of inverse function method for a triangular fuzzy number.

Previous method

The integral value I_T^α for a normal trapezoidal fuzzy number $\hat{A}_i = (a_1, a_2, a_3, a_4; 1)$ as shown in figure 8 can be obtained using equation 3 as proposed by Liou and Wang 1992.

$$I_T^\alpha(\hat{A}_i) = \frac{1}{2}[\alpha(a_3 + a_4) + (1 - \alpha)(a_1 + a_2)] \quad (3)$$

where α is the index of optimism denoting the degree of optimism for decision makers (Liou and Wang 1992).

Vincent and Dat 2014, modified equation 3 to correct for inconsistencies. Equation 4 shows the modified version of equation 3 for a normal trapezoidal fuzzy number $A = (a_1, a_2, a_3, a_4; 1)$ as proposed by Vincent and Dat 2014.

$$I_{1T}^\alpha(\hat{A}_i) = \frac{1}{2}[\alpha(a_3 + a_4) + (1 - \alpha)(a_2 + a_1) - 2x_{min}] \quad (4)$$

$I_{1T}^\alpha(\hat{A}_i)$ is the modified version of equation 3, $x_{min} = \inf P$, $P = \cup_{i=1}^n P_i$, $P_i = \left(\frac{\mu_{\hat{A}_i}}{x} > 0\right)$ as detailed in Vincent and Dat, 2014.

Sam'an et al 2022 improved on equation 4 by using left and right inverse function of trapezoid fuzzy numbers to compensate on the shortcoming of the Vincent and Dat 2014 approach. Equation 5 shows the improved version of equation 4 for a

normal trapezoidal fuzzy number $A = (a_1, a_2, a_3, a_4; 1)$ as proposed by Sam'an et al., 2022.

$$I_{2T}^\alpha(\hat{A}_i) = \frac{1}{2}[\alpha(3a_3 + a_4) + (1 - \alpha)(a_1 + 3a_2) - x_{min}] \quad (5)$$

Improved method

Since triangular fuzzy numbers (TFN's) are special cases of trapezoidal fuzzy numbers when $a_2 = a_3$, equation 5 can be rewritten for a normal triangular fuzzy number $A = (a_1, a_2, a_3; 1)$ as shown in equation 6. It is more expedient working with TFN's due to ease of computation and usefulness in representing information in a fuzzy environment (Jun et al 2013).

$$I_{3T}^\alpha(\hat{A}_i) = \frac{1}{2}[\alpha(3a_2 + a_4) - (1 - \alpha)(a_1 + 3a_2) - x_{min}] \quad (6)$$

Equation 6 can also be written in terms of parameter l (smallest possible value), m (most promising value) and u (the largest possible value that describes a fuzzy event) as described in equation 1 and figure 9, as follows

$$I_{4T}^\alpha(\hat{A}_i) = \frac{1}{2}[\alpha(3m + u) - (1 - \alpha)(l + 3m) - x_{min}] \quad (7)$$

The normalized weight vector $W = (w_1, w_2, \dots, w_n)^T$ of the fuzzy matrix P (equation 2) is calculated using equation 8 (Kabir and Sumi 2014):

$$W_i = \frac{I_{4T}^\alpha(\hat{A}_i)}{\sum_{i=1}^n I_{4T}^\alpha(\hat{A}_i)} \quad i = 1, 2, \dots, n \quad (8)$$

where, W_i is a non-fuzzy number.

3.5.3 Weights Obtained

The calculated weight for each factor is shown

in table 5. The sum of the final weight is 1, a requirement which must be fulfilled during the process of assigning weights.

Table 5: Calculated weight for each input factor

Input factor name	Calculated weights
Rainfall	0.3612
Drainage Density	0.2624
DEM	0.1733
Slope	0.0595
Soil	0.0389
LULC	0.1046
Total	1

3.5.4 Calculating the Fuzzy Consistency Ratio

Comparison relies on subjective judgement which may be biased, hence the need for an evaluation (Xinyi 2016). To determine if consistency was maintained in assigning weights a ratio known as fuzzy consistency ratio (FCR) was calculated. Values of FCR lower than 10% (0.1) are generally considered acceptable. FCR of 0.0650 was obtained. This shows that the pairwise fuzzy comparison matrix of input factors in table 3 is consistent and acceptable.

3.6 Aggregation

Aggregation was carried out using weighted linear combination as shown in equation 9. In weighted linear combination method each standardized factor map is multiplied by its factor weight and everything is thereafter summed.

$$FV = \sum W_i x_i. \quad (9)$$

FV = flood vulnerability, W_i = weight of factor i , and x_i = factor i

Outcome of equation 9 is the map of flood vulnerability across Oyo State as shown in Figure 10.

The final vulnerability map in figure 10 was classified into five vulnerability classes (very high vulnerability, high vulnerability, moderate vulnerability, low vulnerability and very low

vulnerability) using Jenks natural breaks classification method.

4. RESULTS AND DISCUSSION

4.1 Flood vulnerability map

The flood vulnerability map of the study area (Oyo state) is shown in Figure 10. The flood vulnerability map consists of five classes (very low, low, moderate, high and very high vulnerability). Oyo state has thirty-three (33) local government areas (LGA). It can be seen from Figure 10 that six (6) LGAs are highly vulnerable to flooding, they are Oluyole, Ibadan North, Ibadan West, Ibadan North East, Ibadan South West, and Ibadan South East LGAs. Virtually every square kilometre of the above-mentioned LGAs falls under the very high flood vulnerability class in Figure 10. These six LGA areas fall under the Ibadan metropolis and they are associated with a history of devastating flood occurrences, like the 2011 flood occurrence (Eguaroje et al., 2015). Four LGAs are next in line in the order of vulnerability as they fall under the very high and high flood vulnerability classes. The LGA's are Ona Ara, Egbeda, Ido and Lagelu LGA's. The remaining 23 LGAs have a fair distribution of the various flood vulnerability classes across their land mass.

Hotspots for probable flooding are areas under very high vulnerability classes and high vulnerability classes. In particular, the six LGAs under the very high vulnerability class and the 4 LGAs under the high flood vulnerability class should be on a red alert for probable flooding especially during the rainy season. Effective flood management and mitigation strategies should be on the ground for these areas. Table 6 illustrates the distribution of the various flood vulnerability classes in terms of area covered in square kilometres and their percentage area coverage. Areas that are highly vulnerable to flooding occupy 16.898% of the total surface area of the state. Areas under high flood vulnerability class occupy 26.009% of the total study area and this is the highest percentage area among the five vulnerability classes. Thus adequate flood mitigation and management plans should be on ground.

Table 6. Vulnerability assessment classes in area and percentage area

Flood vulnerability class	Area (sqkm)	Percentage area (%)
Very low	3072.3775	11.1073
Low	5952.826	21.520
Moderate	6766.798	24.463
High	7194.448	26.009
Very high	4674.397	16.898
Total	27660.8465	100%

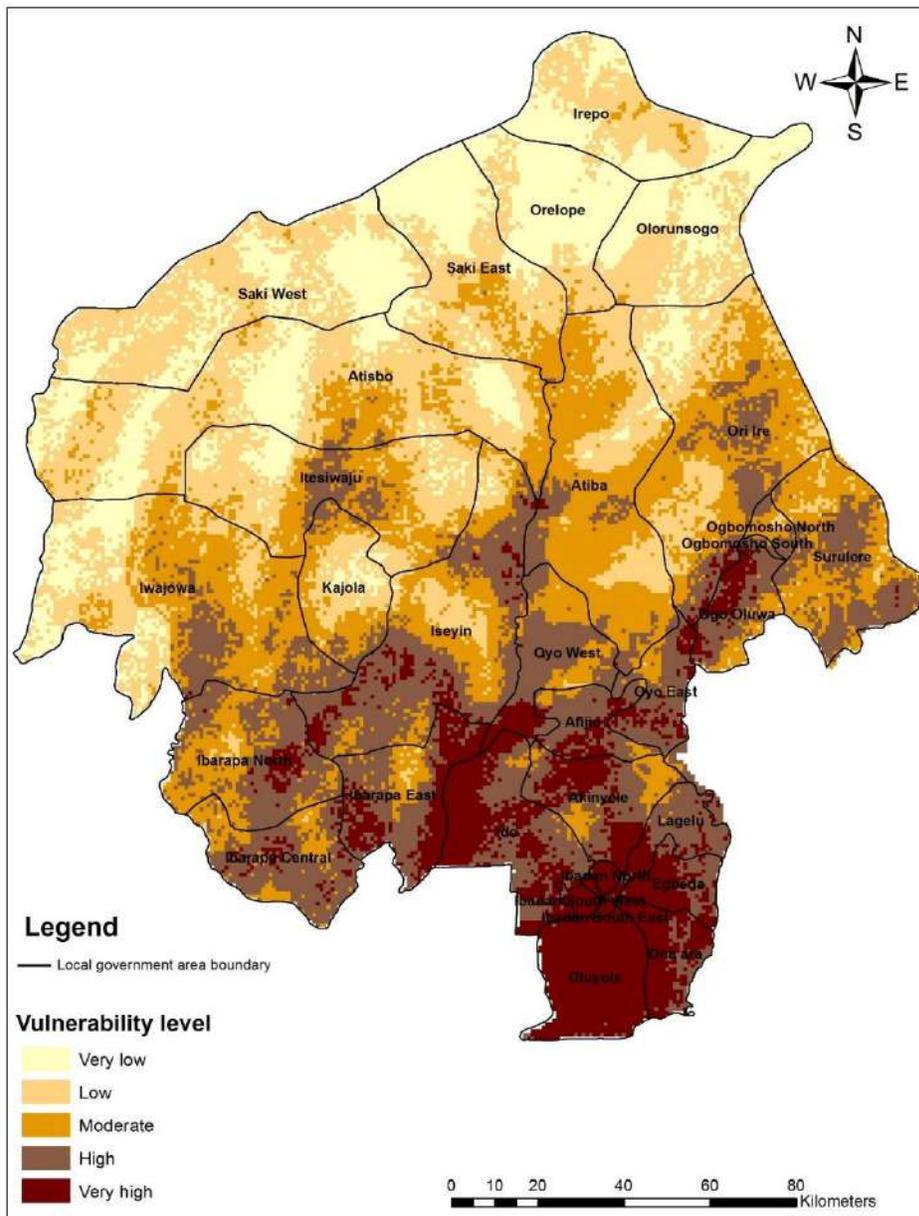


Figure 10. Flood vulnerability map across Oyo state

be seen that Ibadan North, Ibadan Northwest, Ibadan West, Ibadan South West, Ibadan South, Egbeda, Ona Ara, Oluyole, Ido, Akinyele, and Lagelu LGAs constitute the bulk of the settlement areas. Ibadan metropolis (the largest indigenous city in West Africa) is located in the above-listed LGAs. Other LGAs with significant population clusters include Ogbomosho North and Ogbomosho South LGAs, (home to Ogbomosho City), Oyo West and Oyo East LGAs (home to Oyo City) and Iseyin LGA. Table 7 shows the distribution of LULC of the study area in terms of area covered in square kilometres and their percentage area coverage. It can be seen that settlements occupy 4.76% of the total study area, while cultivated lands occupy 20.17% of the study area.

4.3 Flood vulnerability and agricultural cropland

From the LULC map in Figure 11, cultivation is centred majorly around Oyo West, Oyo East, Ogo Oluwa, Iseyin and Atiba LGA. Others include Afijo, Sarki East, Orelapo, Irepo, Ibarapa North, central and East LGAs. Figure 13 shows the overlay of cultivated lands from the LULC map of Figure 11 on the flood vulnerability map of Figure 10. The resultant map (Figure 13) shows the vulnerability of cultivated lands to flood vulnerability within the study area. The majority of the LGAs with large cultivation/cultivated agricultural lands fall under areas majorly classified as moderate flood vulnerability. Exceptions are Oyo West, Ogo Oluwa, Ibarapa East and Iseyin LGA's which are majorly agricultural areas but a substantial portion of cultivation in those areas falls under very high/high flood vulnerability classes. Early warning systems should be a top priority for these LGAs (Oyo West, Ogo Oluwa, Ibarapa East and Iseyin LGAs) to minimize the effects of potential flooding and subsequent reduction in food production.

4.4 Flood vulnerability and human settlements

Flooding becomes more disastrous when it affects human settlements. Identifying potential human settlements that are highly vulnerable to flooding is very important. Figure 13 shows the overlay of settlement from the LULC map of

Figure 11 to the flood vulnerability map of Figure 10. This map (Figure 13) shows the vulnerability of human settlements to flooding. It can be seen from Figure 13 that the Ibadan metropolis (Ibadan north, Ibadan northwest, Ibadan west, Ibadan south west, Ibadan south east, Egbeda, Ona ara, Oluyole, Ido, Akinyele, and Lagelu LGA's) falls majorly under areas classified as very high/high vulnerability to flooding. The history of major flooding in these areas is well-recorded in literature (Ajibade et al., 2021, Eguaroje et al., 2015). Adequate measures such as early warning systems, elimination of waste disposal along waterways, education, adequate and free-flowing water channels, and proper urban planning and enforcement should be embarked upon to mitigate the disastrous effects of flooding in these areas.

4.5 Flood vulnerability and road infrastructure

Flooding can cause massive damage to road infrastructure leading to associated economic losses (He et al., 2022; Singh et al., 2018). Thus it is important to assess road networks' vulnerability to flooding for sustainable economic development (Papilloud et al 2020, Singh et al 2018). Highlighting vulnerable road networks will aid in the implementation of appropriate road maintenance strategies, designs for future road networks and sustainable flood risk management. Figure 14 shows the overlay of road infrastructure (paved road networks only) on the flood vulnerability map of the study area. Road infrastructure vulnerability is then determined based on the spatial location of the road network within the five vulnerability classes in the flood vulnerability map of Figure 10. The bulk of the road networks within the study area are located within Ibadan, Ogbomosho and Oyo metropolis. Road networks within the Ibadan metropolis are highly vulnerable to flooding as the Ibadan metropolis falls under areas classified as highly vulnerable to flooding. Road infrastructure within the Oyo and Ogbomosho metropolis ranges from high to moderate vulnerability to flooding. It is crucial that when designing and constructing paved roads within Ibadan metropolis adequate measures should be taken to tackle probable flooding and subsequent effects of flooding on

the road networks.

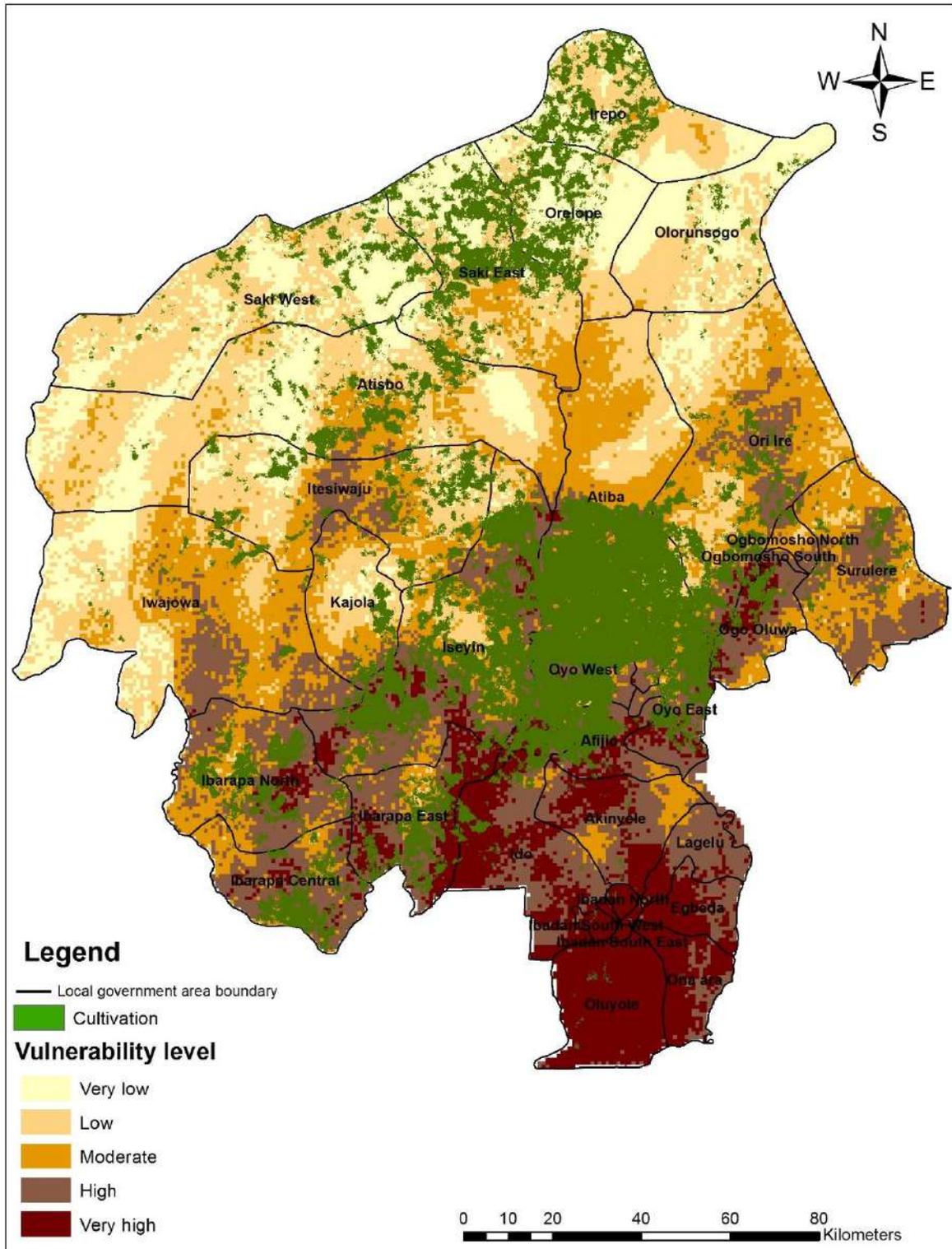


Figure 12. Cultivated lands overlaid on the flood vulnerability map of the study area.

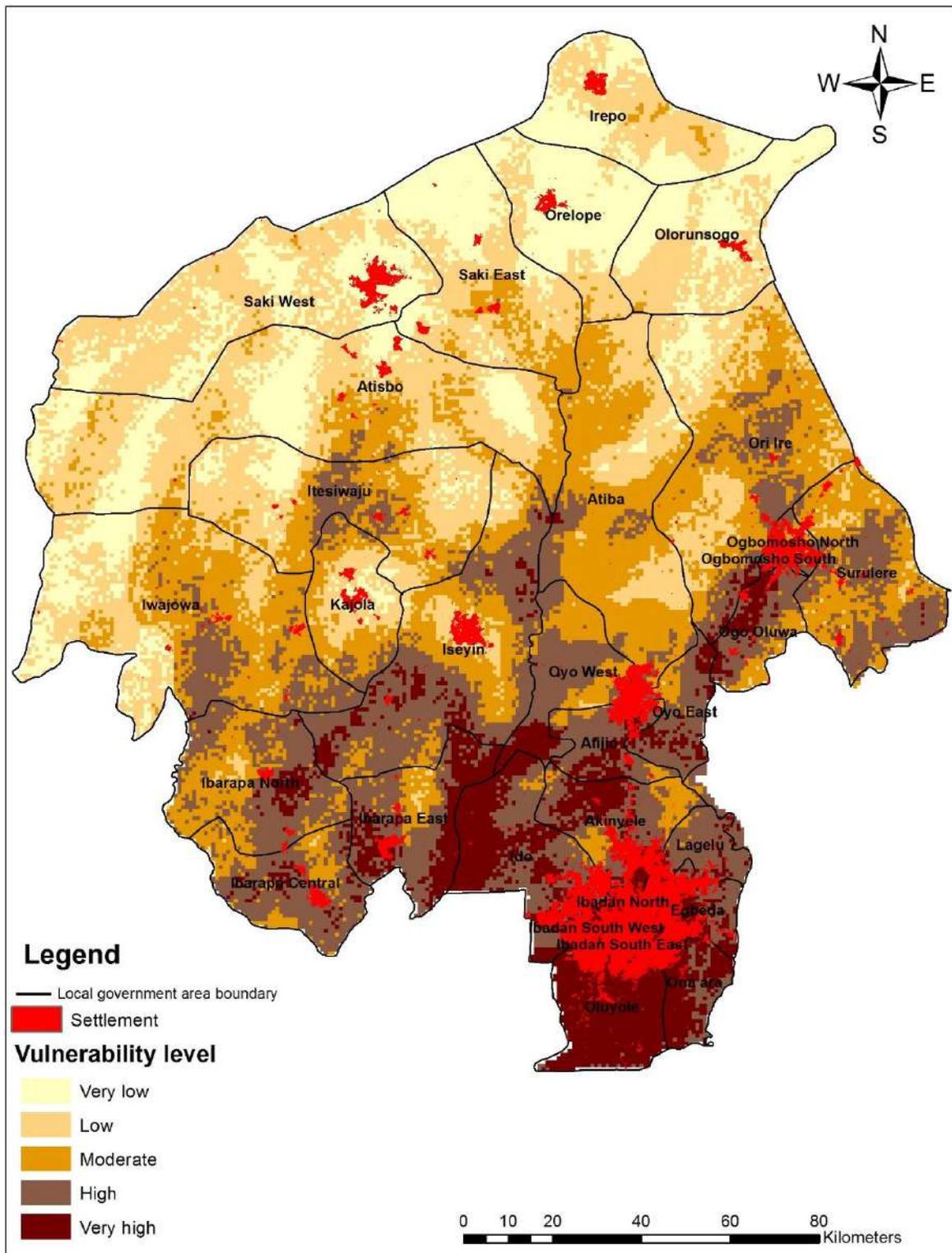


Figure 13. Settlement overlaid on Flood vulnerability map of the study area

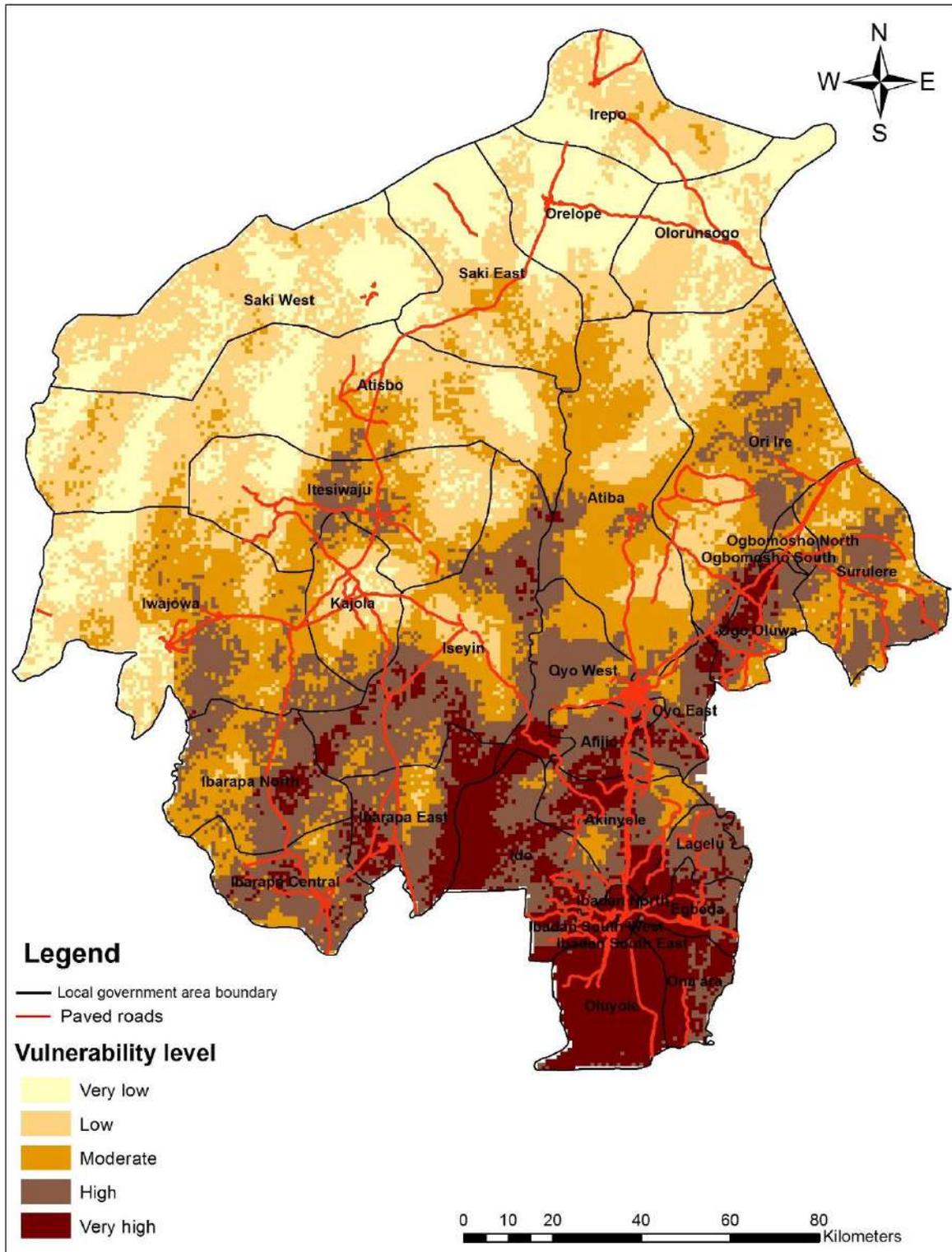


Figure 14. Paved road infrastructure overlaid on Flood vulnerability map of the study area

4.6 Study limitations

Triangular Fuzzy Numbers (TFNs) was used in this study because of their computational simplicity. This comes at a cost of reduced levels of accuracy. Higher fuzzy numbers (such as heptagonal, octagonal and Decagonal fuzzy numbers) where the approximated values are gotten with more accuracy can be used in future works.

5. Conclusion

In this study a Geographic Information System (GIS) based flood vulnerability assessment using integral value of inverse function ranked, Fuzzy Analytical Hierarchical Process (FAHP) to improve the decision-making process in the MCDM process and ensure accurate computation of flood vulnerability assessment for Oyo state was presented. Six flood causative factors (elevation, slope, soil, rainfall, drainage density and LULC information) were used as input criteria into the MCDM technique. Weights were generated using the improved integral value ranked Fuzzy-AHP technique. This technique uses both the left and right inverse functions of a triangular membership function with an index of optimistic function to derive the weight for each input criterion. The generated weights for each of the six causative factors were aggregated to produce a flood vulnerability map for the study area using GIS tools.

The study reveals that the Ibadan metropolis which covers Ibadan north, Ibadan northwest, Ibadan west, Ibadan south west, Ibadan south east, Egbeda, Ona Ara, Oluyole, Ido, Akinyele, and Lagelu LGA's is highly prone to flooding. As it falls majorly under areas classified as very high/high vulnerability to flooding. Similarly, the Ibadan metropolis has the largest population cluster in Oyo state. Thus, standby measures should be on the ground to tackle flood and its subsequent effects on lives, properties and road infrastructures within the Ibadan metropolis and other relative hotspots within the state. Oyo West, Ogo Oluwa, Ibarapa East and Iseyin LGAs are majorly agricultural areas that fall under very high/high flood vulnerability classes. Early warning systems should be a top priority for these LGAs (Oyo West, Ogo Oluwa, Ibarapa

East and Iseyin LGAs) to minimize the effects of potential flooding and subsequent reduction in food production in these areas.

The resultant vulnerability maps (agricultural, settlement and road infrastructure flood vulnerability maps) obtained from the flood vulnerability assessment serves as an early warning system that could be further developed to assist stakeholders in minimizing climate change-induced flood disaster on road infrastructures, food security, risk to lives and properties in Oyo state. Future research works will focus on using higher fuzzy numbers and integrating artificial intelligence and optimization algorithms into the MCDM process to further enhance accuracy.

REFERENCES

- Adeyemi, O. (2021). The association of mobile phone addiction proneness and self-reported road accident in Oyo State, Nigeria. *Journal of technology in behavioral science*, 6(3), 486-491.
- Ahmed, F. and Kilic, K. (2015) 'Modification to fuzzy extent analysis method and its performance analysis', in *2015 International Conference on Industrial Engineering and Systems Management (IESM)*, IEEE, October, pp.435-438.
- Afsari, R., Nadizadeh Shorabeh, S., Kouhnavard, M., Homae, M., & Arsanjani, J. J. (2022). A spatial decision support approach for flood vulnerability analysis in urban areas: A case study of Tehran. *ISPRS International Journal of Geo-Information*, 11(7), 380.
- Chang, D.Y. (1996) 'Applications of the extent analysis method on fuzzy AHP', *European Journal of Operational Research*, Vol. 95, No.3, pp.649-655.
- Ajibade, F. O., Ajibade, T. F., Idowu, T. E., Nwogwu, N. A., Adelodun, B., Lasisi, K. H., ... & Adewumi, J. R. (2021). Flood-prone area mapping using GIS-based analytical hierarchy frameworks for Ibadan city, Nigeria. *Journal of Multi-Criteria Decision Analysis*, 28(5-6), 283-295.

- Ali, S. A., Khatun, R., Ahmad, A., & Ahmad, S. N. (2019). Application of GIS-based analytic hierarchy process and frequency ratio model to flood vulnerable mapping and risk area estimation at Sundarban region, India. *Modeling Earth Systems and Environment*, 5(3), 1083-1102.
- Alimi, S. A., Andongma, T. W., Ogungbade, O., Senbore, S. S., Alepa, V. C., Akinlabi, O. J., ... & Muhammed, Q. O. (2022). Flood vulnerable zones mapping using geospatial techniques: Case study of Osogbo Metropolis, Nigeria. *The Egyptian Journal of Remote Sensing and Space Science*, 25(3), 841-850.
- Areola, F. (2020). Local Adaptation Strategies in Combating Flooding in Fisheries and Aquaculture in Nigeria. In *Handbook of Climate Change Management: Research, Leadership, Transformation* (pp. 1-19). Cham: Springer International Publishing.
- Atijosan, A. O., Isa, I., & Abayomi, A. (2021). Urban flood vulnerability mapping using integral value ranked fuzzy AHP and GIS. *International Journal of Hydrology Science and Technology*, 12(1), 16-38.
- Chen, J., Huang, G., & Chen, W. (2021). Towards better flood risk management: Assessing flood risk and investigating the potential mechanism based on machine learning models. *Journal of environmental management*, 293, 112810.
- Daramola, D., Kilasho, A., & Oluborode, J. (2022). Assessment of Timber Contractors Contribution To Forest Development In Iseyin And Oyo East Local Government Areas, Oyo State, Nigeria. *Management of Sustainable Development*, 14(2), 64-69.
- Echendu, A. J. (2022). Flooding in Nigeria and Ghana: Opportunities for partnerships in disaster-risk reduction. *Sustainability: Science, Practice and Policy*, 18(1), 1-15.
- Ekmekcioğlu, Ö., Koc, K., & Özger, M. (2021). District based flood risk assessment in Istanbul using fuzzy analytical hierarchy process. *Stochastic Environmental Research and Risk Assessment*, 35, 617-637.
- Eguaroje, O., Alaga, T., Ogbole, J., Omolere, S., Alwadood, J., Kolawole, I., ... & Ajileye, O. O. (2015). Flood vulnerability assessment of Ibadan city, Oyo state, Nigeria. *World Environment*, 5(4), 149-159.
- Food and Agriculture Organization (FAO), (2021). *The Impact of Disasters and Crises on Agriculture and Food Security: 2021*.
- Gigović, L., Pamučar, D., Bajić, Z. and Drobnjak, S. (2017) 'Application of GIS-interval rough AHP methodology for flood hazard mapping in urban areas', *Water*, Vol. 9, No. 6, p.360.
- He, Y., Ma, D., Xiong, J., Cheng, W., Jia, H., Wang, N., ... & Yang, G. (2022). Flash flood vulnerability assessment of roads in China based on support vector machine. *Geocarto International*, 37(21), 6141-6164.
- <https://www.premiumtimesng.com/agriculture/agric-news/436380-nearly-80-of-nigerian-farmers-affected-by-floods-drought-in-2020-report.html>
- <https://oxfordbusinessgroup.com/analysis/untapped-potential-despite-many-difficulties-opportunities-agriculture-are-numerous>.
- Ighile, E. H., Shirakawa, H., & Tanikawa, H. (2022). A Study on the Application of GIS and Machine Learning to Predict Flood Areas in Nigeria. *Sustainability*, 14(9), 5039.
- Jun, K. S., Chung, E. S., Kim, Y. G., & Kim, Y. (2013). A fuzzy multi-criteria approach to flood risk vulnerability in South Korea by considering climate change impacts. *Expert Systems with Applications*, 40(4), 1003-1013.
- Kabir, G. and Hasin, M. (2012) 'Multiple criteria inventory classification using fuzzy analytic hierarchy process', *International Journal of Industrial Engineering Computations*, Vol. 3, No. 2, pp.123-132.
- Kabir, G. and Sumi, R.S. (2014) 'Integrating fuzzy analytic hierarchy process with PROMETHEE method for total quality

- management consultant selection', *Production & Manufacturing Research*, Vol. 2, No. 1, pp.380–399.
- Kandari, S., Pasupuleti, R. S., & Samaddar, S. (2022). Cultural Systems in Water Management for Disaster Risk Reduction: The Case of the Ladakh Region. *IDRiM Journal*, 11(2), 28-56.
- Liu, J., Xiong, J., Cheng, W., Li, Y., Cao, Y., He, Y., & Yang, G. (2021). Assessment of Flood Susceptibility Using Support Vector Machine in the Belt and Road Region. *Natural Hazards and Earth System Sciences Discussions*, 1-37.
- Liou, T.S. and Wang, M.J.J. (1992) 'Ranking fuzzy numbers with integral value', *Fuzzy Sets and Systems*, Vol. 50, No. 3, pp.247–255.
- Milošević, D. M., Milošević, M. R., & Simjanović, D. J. (2020). Implementation of adjusted fuzzy AHP method in the assessment for reuse of industrial buildings. *Mathematics*, 8(10), 1697.
- Nasiri, H., Yusof, M.J.M., Ali, T.A.M. and Hussein, M.K.B. (2018) 'District flood vulnerability index: urban decision-making tool', *International Journal of Environmental Science and Technology*, Vol. 16, No. 5, pp.1–10.
- Nsangou, D., Kpoumié, A., Mfonka, Z., Ngouh, A. N., Fossi, D. H., Jourdan, C., ... & Ngoupayou, J. R. N. (2022). Urban flood susceptibility modelling using AHP and GIS approach: case of the Mfoundi watershed at Yaoundé in the South-Cameroon plateau. *Scientific African*, 15, e01043.
- Obeta, C.M. (2014) 'Institutional approach to flood disaster management in Nigeria: need for a preparedness plan', *British Journal of Applied Science & Technology*, Vol. 4, No. 33, pp.4575–4590.
- O'Donnell, E. C., & Thorne, C. R. (2020). Drivers of future urban flood risk. *Philosophical Transactions of the Royal Society A*, 378(2168), 20190216.
- Olowe, F. J. (2021). Spatial prediction of flood susceptible areas using machine learning approach: a focus on West African region (Doctoral dissertation).
- Oskorouchi, H. R., & Sousa-Poza, A. (2021). Floods, food security, and coping strategies: Evidence from Afghanistan. *Agricultural Economics*, 52(1), 123-140.
- Oyewole, S. O., Afolami, C. A., Obayelu, A. E., & Adeofun, C. O. (2022). Effect of Sustainable Agricultural Practices on Production Efficiency of Maize Farmers in Oyo and Ogun States of Nigeria. *The Journal of Developing Areas*, 56(4), 121-136.
- Ouma, Y.O. and Tateishi, R. (2014) 'Urban flood vulnerability and risk mapping using integrated multi-parametric AHP and GIS: methodological overview and case study assessment', *Water*, Vol. 6, No. 6, pp.1515–1545.
- Papilloud, T., Röthlisberger, V., Loreti, S., & Keiler, M. (2020). Flood exposure analysis of road infrastructure—Comparison of different methods at national level. *International journal of disaster risk reduction*, 47, 101548.
- Pallard, B., Castellarin, A. and Montanari, A. (2009) 'A look at the links between drainage density and flood statistics', *Hydrology and Earth System Sciences*, Vol. 13, No. 7, pp.1019–1029.
- Rahmati, O., Pourghasemi, H.R. and Zeinivand, H. (2015) 'Flood susceptibility mapping using frequency ratio and weights-of-evidence models in the Golastan Province, Iran', *Geocarto Int.*, DOI:10.1080/10106049.2015.1041559.
- Ruan, J., Shi, P., Lim, C.C. and Wang, X. (2015) 'Relief supplies allocation and optimization by interval and fuzzy number approaches', *Information Sciences*, Vol. 303, No. 1, pp.15–32.
- Sam'an, M. (2021, June). An improved ranking method for fuzzy numbers using integral value of inverse function. In *Journal of Physics: Conference Series* (Vol. 1918, No. 4, p.042147). IOP Publishing.
- Selvam, R. A., & Antony Jebamalai, A. R. (2023). Application of the analytical hierarchy process (AHP) for flood

- susceptibility mapping using GIS techniques in Thamirabarani river basin, Srivaikundam region, Southern India. *Natural Hazards*, 1-19.
- Şen, C.G. and Çınar, G. (2010) 'Evaluation and pre-allocation of operators with multiple skills: a combined fuzzy AHP and max-min approach', *Expert Systems with Applications*, Vol. 37, No. 3, pp.2043–2053.
- Singh, P., Sinha, V. S. P., Vijhani, A., & Pahuja, N. (2018). Vulnerability assessment of urban road network from urban flood. *International journal of disaster risk reduction*, 28, 237-250.
- Tahri, M., Maanan, M., Maanan, M., Bouksim, H. and Hakdaoui, M. (2017) 'Using fuzzy analytic hierarchy process multi-criteria and automatic computation to analyse coastal vulnerability', *Progress in Physical Geography*, Vol. 41, No. 3, pp.268–285
- Tudunwada, I. Y., & Abbas, A. (2022). Flood vulnerability mapping and prediction for early warning in Jigawa State, Northern Nigeria, using geospatial techniques. *International Journal of Disaster Risk Reduction*, 79, 103156.
- Vincent, F. Y., & Dat, L. Q. (2014). An improved ranking method for fuzzy numbers with integral values. *Applied soft computing*, 14, 603-608.
- Week, D. A., & Wizer, C. H. (2020). Effects of flood on food security, livelihood and socio-economic characteristics in the flood-prone areas of the core Niger Delta, Nigeria. *Asian Journal of Geographical Research*, 3(1), 1-17.
- Yildirim, E., & Demir, I. (2022). Agricultural flood vulnerability assessment and risk quantification in Iowa. *Science of the Total Environment*, 826, 154165.