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Flood-prone area mapping using GIS-based analytical hierarchy frameworks for Ibadan city, Nigeria

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Abstract

Flood is one of the highly pronounced ruinous naturally occurring environmental hazards in which human lives and properties are gravely endangered. This study assessed areas prone to flood in Ibadan City, Nigeria. The study applied two multi-criteria analysis approach—Analytical Hierarchy Process (AHP) and the Fuzzy Analytical Hierarchy Process (FAHP) with the aid of GIS. Ten geomorphological physical characteristics agreed upon by experts as the major factors influencing the susceptibility of an area to floods formed the criteria maps used in this study. The natural breaks and geometrical interval clustering techniques were utilised to group the final flood-prone area maps into five categories—very low, low, moderate, high, and very high. The result indicated that over 50% of the study area either have low or moderate susceptibility to flooding. The clustering techniques showed some slight differences in the flood classifications where natural breaks consistently grouped more areas into the “very high” category and relatively fewer areas to “very low” category in comparison to the geometrical interval technique. Overall, at least 451 km² (about 15% of Ibadan) is highly or very highly prone to floods, and these areas are mainly concentrated in the urban and semi-urban regions of the study area. The findings and maps developed in this study would adequately serve as a planning guide for the policymakers on urban development and flood risk management to achieve sustainable development and management.

KEYWORDS

analytical hierarchy process, clustering techniques, flood-prone areas, fuzzy analytical hierarchy process, GIS, multi-criteria analysis

1 | INTRODUCTION

Natural disasters have terrifyingly been escalating in many parts of the world, and their impacts have become one of the most subjects of concern in recent times. Such cataclysms include soil erosion, earthquakes, wildfires, and floods, whose occurrences customarily result in immeasurable losses of lives and properties every year

(Vorogushyn et al., 2012; Sharif et al., 2016; Tehrany & Kumar, 2018; Ajibade, Nwogwu, Adelodun, et al., 2020). Flood is one of the most common and catastrophic disasters around the globe. It takes place after substantial precipitation, especially one with instantaneous build-up and the contributing runoff flowing from upstream to downstream (Mousavi et al., 2019). Flood refers to any overland flow above urban land that is enough to cause substantial property damage,

transportation obstruction, nuisance, health risks, and even death which include river flood, flash flood, and damages (Grimaldi et al., 2013; Gwary, 2008; Ogunlela & Adelodun, 2014). Wisler and Brater (2009) viewed flood as a life-threatening hydrological event which arises when the infiltration capacity of the soil is lesser than rainfall intensity. Besides the breakneck urbanisation, population growth, and climatological alteration, flooding is as well significantly facilitated by failure of water drainage systems due to low design capacity, poor maintenance, cutback in natural buffering areas (such as wetland), and poor environmental management (Zhang et al., 2017). Besides the fact that flood is a natural phenomenon, both natural and human-made factors promote its occurrence (Sukcharoen et al., 2016). Sudden flooding is intricate to be prognosticated and which are often accompanying by secondary occurrences including mass movements and soil erosion (Grimaldi et al., 2013). Flood is evaluated to be the second most pernicious of all meteorological perils with immense detriments to many societies in many parts of the world as a consequence of great perniciousness on both lives and properties (Adewumi et al., 2017). In the last decade, approximately 40% of the deaths resulting from natural hazards were attributed to floods, from which around 100,000 people have been killed, and existences of 1.4 billion people have been put to distress (Ezemonye & Emeribe, 2011). Between 1980 and 2009, an annual average of about 2.8 billion people was affected by floods across the globe (Doocy et al., 2013). UNISDR (2015) equally reported that between 1995 and 2015, of all the global weather-related menaces, which gave a statistic of affected lives of 2.3 billion persons, floods account for 47%.

Nigeria is among the countries that are frequently affected by floods (Ezemonye & Emeribe, 2011). The persistence flood events affecting different regions and states of the six geopolitical zones (south-south, south-west, south-east, north-central, north-east, and north-west) in the country are customary during the rainy season. Jeb and Aggarwal (2008) affirmed that the major causes of floods in Nigeria include heavy rainfall, water drainage blockages/failures, and dam failures. Apart from droughts, about 90% of destructions are triggered by flood hazards in Nigeria (Adeoye et al., 2009). Ibadan City in Oyo state is one of the recognised floods susceptible areas in the south-western part of Nigeria. The earliest flood event experienced in Nigeria was in Ibadan in 1948 (Adewumi et al., 2017). It is almost customary that above 7.7 million hectares of agricultural land and built-up environments are damaged as a result of flooding in Nigeria annually (Jeb & Aggarwal, 2008). The occurrence of different forms of flood in Nigeria is predominant in those states along the rivers Niger and Benue in which Ibadan city is located (Adeoye et al., 2009; Adewumi et al., 2017; Jeb & Aggarwal, 2008).

To promote sustainable environment and development, flood management and control which are usually feasible only with the use of flood hazard maps are vital not just because floods block society from the pathway out of poverty, but water resources need to be managed appropriately and harnessed as well land requires optimum utilisation (Ajibade, Nwogwu, Ajibade, et al., 2020; Pradhan, 2010). Prediction, preparation, prevention, and damage assessment are the major four flood management steps commonly carried out

(Tehrany et al., 2013). The need for effective flood management has led to the development and use of various methods and hydrological models. In flood susceptible mapping, studies have proven that the inefficiency of most traditional techniques earlier used has prompted the development of better and efficient ones, and their combinations also yield more reliable results. Hydrological models such as HYDROTEL (Fortin et al., 2001), WetSpa (Liu & De Smedt, 2004), and SWAT (Jayakrishnan et al., 2005) have been combined with remote sensing and geographic information system for collecting data as well as spatial analysis. However, more efficient and automated techniques are still desired to solve the drawbacks of the traditional hydrological techniques (Li et al., 2012). Tehrany et al. (2013) stated that Townsend and Walsh (1998) is one of the ground-breaking studies that confirmed the possibility of flood prediction using RS modelling in a GIS environment, and many works in literature have reported various methods using these techniques. Good results were obtained using the techniques, but some limitations were observed, which require some improvement (Matgen et al., 2007).

Additionally, some popular methods that have been employed in flood susceptibility judgement include; artificial neural network (ANN), and AHP. Others are statistical methods such as logistic regression model (LR) and frequency ratio (FR) (Tehrany et al., 2013). These statistical methods are characteristically built on linear hypotheses, which are not fit for catchment studies with nonlinear structures (Liu & De Smedt, 2004). Hence, the drawbacks associated with each of these methods led to the desire, development, combination, and use of advanced and efficient methods. Although numerous studies have worked on flood susceptibility mapping and flood prediction, some useful techniques such as evidential belief function (EBF) and some ensemble algorithms have not been applied (Tehrany & Kumar, 2018). The expertise of RS and GIS has revolutionised hydrology and flood management studies as they can fulfil the necessities at each phase entirely (Tehrany & Kumar, 2018; Van Westen, 2013). Furthermore, the incorporation of GIS and AHP has been proved to be an efficient means to resolve issues in several fields of study such as landfill site selection problem (Adewumi et al., 2019; Ajibade et al., 2019); complex healthcare decision-making problems (Glaize et al., 2019); temporary shelter site selection for humanitarian relief (Trivedi & Singh, 2019); water resources management (Ajibade et al., 2021; Chowdary et al., 2013); landslides mapping (Adewumi et al., 2016; Feizizadeh & Blaschke, 2013); and pollution (Negi & Jain, 2008). Specifically, numerous studies have employed AHP, FAHP or GIS modelling for the estimation of flood risk, flood hazard, flood-prone zones, and other natural hazards (Papaioannou et al., 2015; Park et al., 2013; Stefanidis & Stathis, 2013; Tehrany et al., 2013; Zou et al., 2013).

Flood management studies try to find areas predisposed to flooding that should be avoided in impending development planning. As a large-scale phenomenon, the precarious nature of flood events requires the identification of susceptible flood risk areas in watersheds or regions to aid appropriate decision making in implementing flood control strategies. This study, therefore, aims to; (1) develop flood risk maps for identifying the flood-prone areas in the study area,

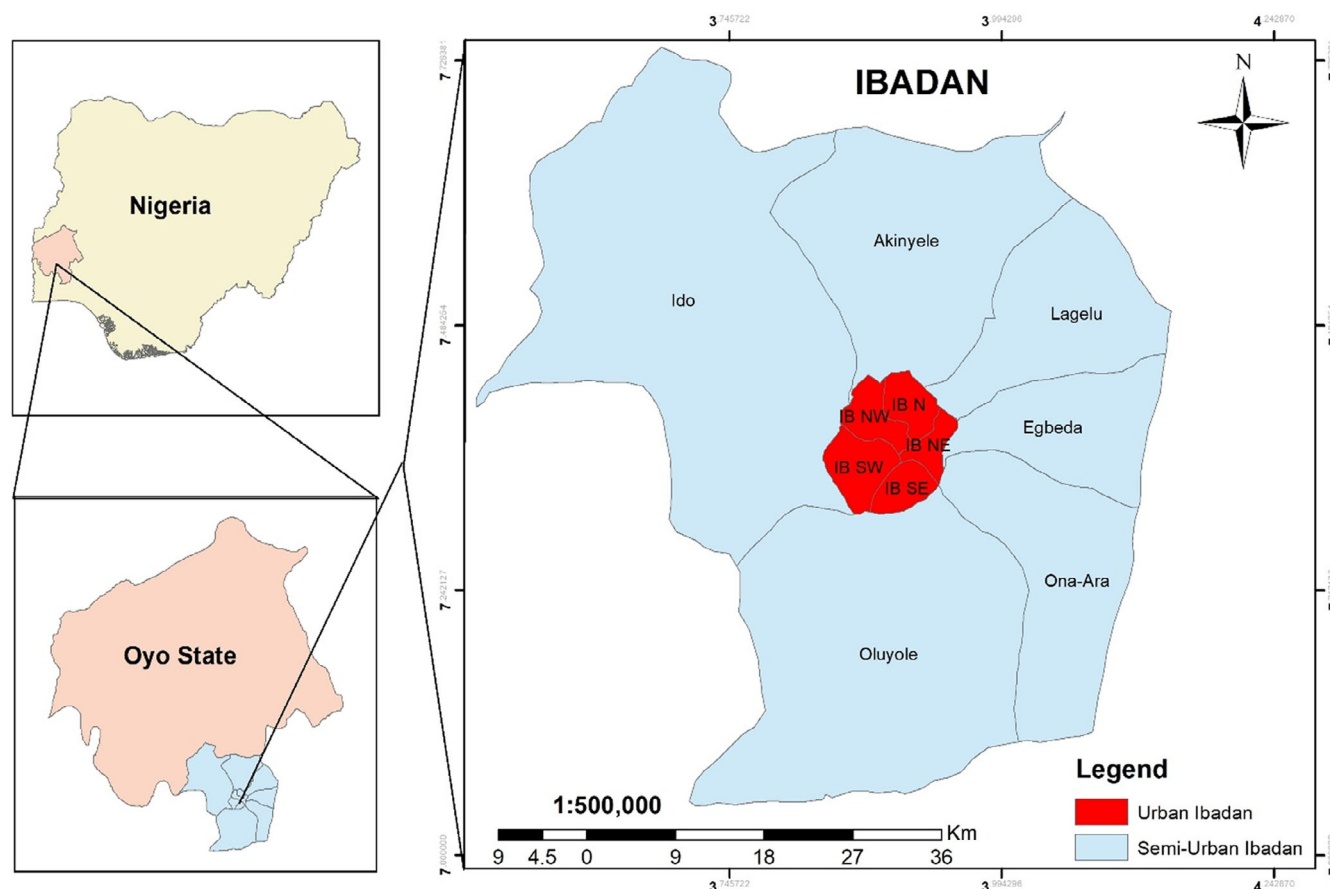


FIGURE 1 Map of Ibadan City, Oyo state, Nigeria

(2) compare two multi-criteria analysis techniques (AHP and FAHP) as well as two clustering techniques (natural breaks and geometric intervals) the process of mapping flood-prone areas using the GIS-approach, (3) identify factors that cause flooding, classify and make spatial distribution assessment of the impact of the factors on flooding, and produce maps of flooding amount and vulnerability in the Ibadan city, Nigeria, using geographical information system and remote sensing integrated with fuzzy logic.

2 | BRIEF DESCRIPTION OF THE STUDY AREA

Ibadan is the capital of Oyo state, Nigeria, and the most populous city in the state with a population of over 3 million. Its map is as shown in Figure 1. It is the third most populous city in Nigeria, after Lagos and Kano. It is the country's largest city by geographical area. Ibadan lies between longitude 3°30' E–4°10' E and latitude 6°50' N–7°50' N and characterised mostly by lowlands which are punctuated by rocky outcrops and series of hills. These outcrops are mainly granitic. Three major landforms of hills, plains, and river valleys dominate the whole landscape of the region. The average elevation is 230 m above mean sea level. The metropolis is drained by three main rivers which include;

River Ogunpa, River Ona, and River Ogbere with their several tributaries including Omi, Kudeti, Alaro, and Alapata. The administrative divisions comprise 11 local government areas (LGAs), 5 of which are urban while the remain 6 are considered semi-urban or less-city areas (Figure 1). Ibadan has a tropical wet and dry climate and according to Köppen climate classification it is classified as Aw, with a lengthy wet season and relatively constant temperatures throughout the year. Ibadan's wet season runs from March through October, though August has a break that lasts for some days without precipitation. November to February forms the city's dry season, during which Ibadan experiences the typical West African harmattan. The mean total rainfall for Ibadan is 1420.06 mm. there are two peaks for rainfall, June and September. The mean maximum temperature is 26.46° C, minimum temperature of 21.42° C and the relative humidity is 74.55%.

3 | METHODOLOGY

The multi-criteria analysis (MCA) framework is a widely used analysis technique for vulnerability mapping for floods (Komolafe et al., 2020; Musungu et al., 2012), groundwater pollution (Ezekiel et al., 2016), land-use suitability analysis (Chen, 2014) and many other applications. In this study, two MCA frameworks based on the respective relative

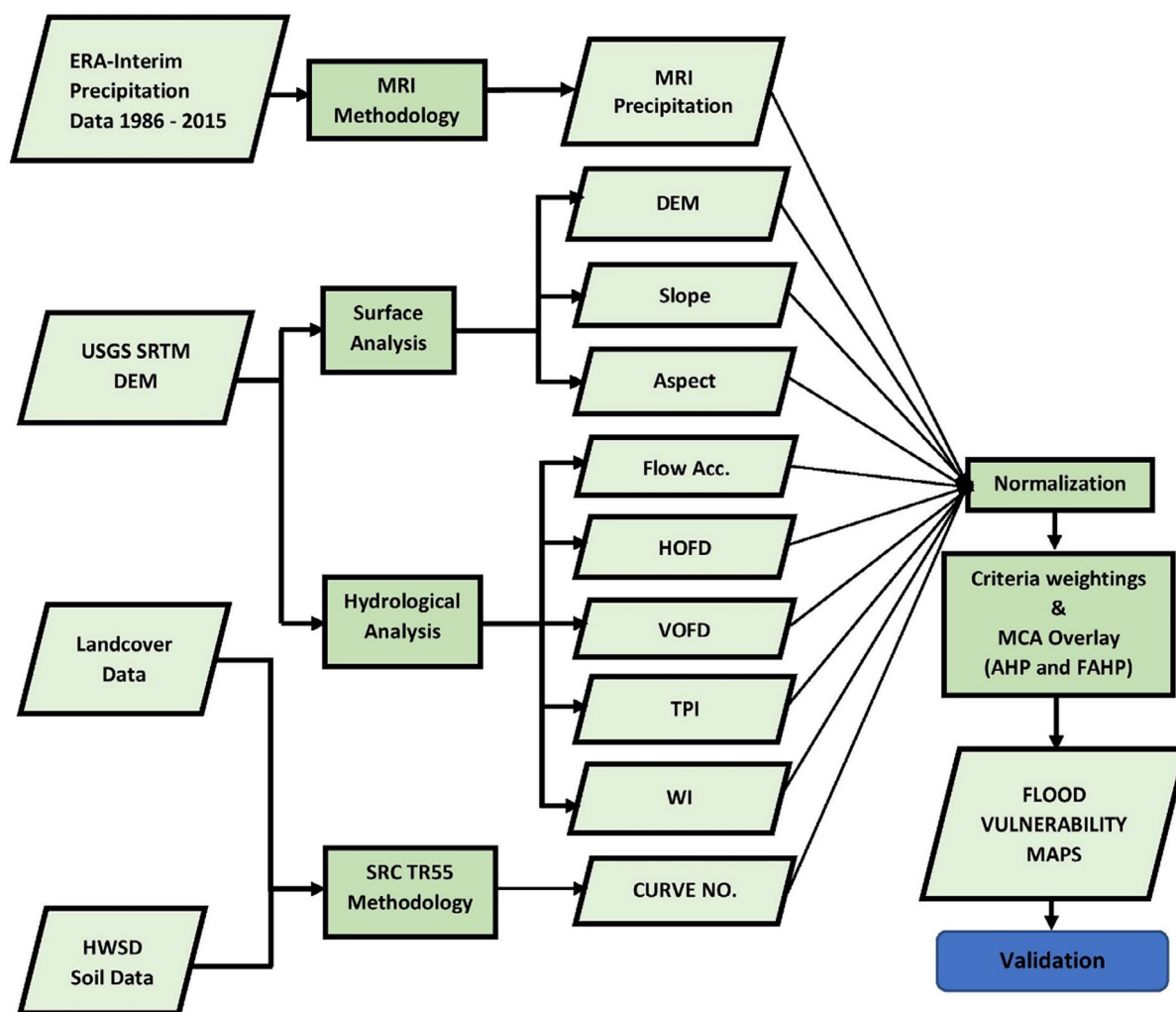


FIGURE 2 Methodology flow chart

weights of flood vulnerability criteria and the consistency ratios of these criteria were applied with the aid of GIS. The two frameworks are the AHP and the Fuzzy Analytical Hierarchy Process (FAHP). The AHP uses hierarchical structures to represent a problem, and subsequently, develop priorities for alternatives from observations made in the structure (Saaty, 1980). The FAHP further incorporates consistent fuzzy numbers and triangulation with different linguistic scales of importance. Detailed explanations of AHP and FAHP multi-criteria analysis frameworks and their application in environmental analyses are found in previous studies (Gigović et al., 2017; Mukherjee & Singh, 2019; Ouma & Tateishi, 2014; Papaioannou et al., 2015). The AHP and FAHP were both explored in this study with the main aim of identifying subtle differences in results, and in the long run contribute science-based information on how each method performs under different conditions.

The criteria adopted for the study were based on expert opinions on the most decisive environmental factors impacting the vulnerability of an area to flooding. The expert opinions were formed through a presentation at a scientific conference on flooding where 32 flood-related factors were shrunk down to the 10 most important factors

(Papaioannou et al., 2011). These factors were compared with the ones adopted by several other cases studies on flood-prone area mapping (Cabrera & Lee, 2019; di Baldassarre et al., 2009; Elkhachy, 2015; Yahaya et al., 2010). These criteria were normalised using the min-max methodology using map algebra and raster spatial analysis tools through GIS. The relative weights and consistency ratios of the AHP and FAHP were then applied and overlaid to produce the final flood-prone area maps. Finally, two GIS-based cluster methods were applied for grouping the generated maps into five distinct vulnerability groups ranging from very low to very high. The validation of the maps was done with historically flooded areas and the use of different clustering techniques. A methodology flow chart showing the steps taken are presented in Figure 2.

3.1 | Data acquisition

The success of flood-prone area mapping largely depends on the choice of criteria used as input data. Hence, in this study, the criteria adopted are based on the expert analysis of 32 potential

geomorphological attributes related to flooding where 10 most pivotal criteria were identified (Papaioannou et al., 2015). The 10 criteria include; (1) digital elevation (2) aspect, (3) slope, (4) flow accumulation, (5) horizontal overland flow distance (HOFD), (6) vertical overland flow distance (VOFD), (7) topographic position index (TPI), (8) wetness index (WI), (9) curve number (CN), and (10) modified Fourier index (MFI). To compute these criteria maps, the data obtained include the DEM, soil data, land cover imagery, and precipitation data.

3.1.1 | Digital elevation model (DEM)

The 30 m resolution Shuttle Radar Topography Mission (SRTM) DEM imagery covering Ibadan was downloaded from the United States Geological Survey (USGS) website (USGS, n.d.). The DEM cuts across two grids—Path 191, Row 55, and Path 191, Row 56 of the USGS grid system. The DEMs for the two grids were downloaded and mosaicked. Subsequently, the study area's DEM was clipped from the mosaicked image. This imagery contributed directly or indirectly to the creation of seven of the criteria maps.

3.1.2 | Soil data

Soil data was gotten from the Harmonized World Soil Database (HWSD) viewer. HWSD is the result of a collaboration between the Food Agriculture Organization (FAO) with International Institute for Applied Systems Analysis (IIASA) ISRIC-World Soil Information, Institute of Soil Science, Chinese Academy of Sciences, and the Joint Research Centre of European Commission (FAO, 2020). The data was pre-processed, digitised, and converted to a 30 m resolution raster format.

3.1.3 | Landcover imagery

The model continental landcover map of Africa developed by the climate change initiative (CCI) of the European Space Agency (ESA) was downloaded used for this study. The landcover map which has a 20 m resolution is based on a yearlong Sentinel-2 A aggregated data over Africa from December 2015 to December 2016 (Abellavia, 2018). One of the main applications of Sentinel-2 A is the area of land monitoring and climate change (Sentinel Online, n.d.). The classification of the landcover map is based on the CORINE classification system.

3.1.4 | Precipitation data

Gridded data for Ibadan was acquired from ERA-Interim for the period of 30 years from 1986 to 2015 (Dee & National Center for Atmospheric Research Staff, 2019). The average climatic data were used to represent the rainfall distribution pattern in Ibadan.

3.2 | Criteria classification and maps creation

A crucial aspect of flood-prone area mapping is the criteria maps used for the classification. As highlighted earlier, the choice of criteria used in this study was based on the aggregation of expert knowledge gleaned from a scientific conference on flood management and several previous case studies on flood-prone area mapping (Cabrera & Lee, 2019; di Baldassarre et al., 2009; Elkhachy, 2015; Papaioannou et al., 2011, 2015; Yahaya et al., 2010) and the process of developing each criteria map is discussed. Raster files of 30 m resolution were generated for each criterion using the map algebra and reclassify spatial analyst tools of ArcGIS. Each final criteria map was then normalised using the min-max methodology to ensure uniformity and reduce the subjectivity generally inherent in MCA techniques.

3.2.1 | Digital elevation model

The downloaded void-filled 30 m resolution SRTM was not only one of the raw data used for creating the criteria maps but it was also one of the criteria maps. DEMs represent the elevations of geographical points with respect to mean sea levels where lower elevations are more susceptible to flooding than the contiguous higher elevation points. Therefore, the DEM was reclassified to reflect lower elevations as being more susceptible and vice versa. This was achieved using an inverting the DEM values and finally, the normalisation was done.

3.2.2 | Aspect, slope, and flow accumulation

The creation of the aspect, slope, and accumulation maps were based on the standard procedures using the spatial analyst toolbox of ArcGIS 10.3 (ESRI, 2016). The aspect delineates the downslope cardinal direction of each cell in relation to its neighbours. The value allocation is such that north and south directions represent very low and very high vulnerabilities respectively. The slope represents the gradient (maximum rate of change in elevation) from each cell of the raster surface in percentages or degrees. Steeper slopes cause more erosion but high runoff rates while gentler slopes are more susceptible to deposition and floods. Flow accumulation raster highlights the amount of flow accumulated in each raster cell based on the cumulative weights of the preceding cells. Flow accumulation is directly proportional to vulnerability to floods. Finally, these criteria maps were all normalised.

3.2.3 | Horizontal overland flow distance (HOFD)

This is the computed distance of each cell to the nearest drainage point based on the flow paths in the flow direction maps. However, overland flow distances are not Euclidean distances but rather hydraulic distances that take the real movement of water from cell to

cell. The creation of the HOFD is based on the SAGA flow routing algorithm, using the DEM as the base data as described in (Olaya, 2004).

3.2.4 | Vertical overland flow distance (VOFD)

The VOFD criteria map is not based on flow distance but the difference in vertical elevations between the DEM and the calculated channel flow. The two steps for determining the VOFD are highlighted by (Olaya, 2004). As with the HOFD, the DEM also acts as the base data for the computation of the VOFD.

3.2.5 | Topographic position index (TPI)

The TPI criterion identifies which landforms are valleys, ridges, or flats in the study area where valleys and ridges represent the positive and negative TPIs, respectively. Flats and constant slope areas are areas with TPI values close to zero. The TPI map compares the elevations of the cells in a DEM to the mean elevation of the specified neighbourhood of the cells (Weiss, 2001). The step-by-step process of creating the TPI criteria map from a DEM in ArcGIS is outlined in (ESRI, 2019). Hence, in this study, the DEM acts as the base data for the computation of the TPI. The TPI is calculated based on the relative size of the study area, hence, a cell size of radius 5 (100 m) was adopted. It was also done to account for the distance to rivers through a buffering technique. Finally, the TPI map was normalised.

3.2.6 | Wetness index (WI)

The WI criteria used is similar to the Topographic WI in that they both quantify the influence of topography on hydrological processes. The methodology, however, is based on the SAGA wetness index which does not treat flows as thin films as observed in common algorithms (Boehner et al., 2002). The advantages of these WI are that cells having small vertical distances to a channel but located in valley floors are predicted more realistically, show higher potential for soil moisture, and accounts for the dependence of each cell on neighbouring maximum values by using a slope dependent equation (Papaioannou et al., 2015). The slope, flow direction and flow accumulation raster files were used for creating the normalised weighted index map.

3.2.7 | Curve number (CN)

The CN which was created by the Natural Resources Conservation Service of the USDA is the most sensitive criterion for flood-prone area mapping. This component accounts for the permeability characteristics of the surface. Impervious surfaces do not allow for infiltration, hence, in some cases, nearly all the precipitation hitting the surface is converted into runoff which subsequently builds up into

floods. The two main datasets used for creating the CN are the land-cover and soil maps. The first step in the methodology for developing the CN number involves the classification of the soil maps into four hydrologic soil groups (HSG) which are based on minimum infiltration rate. Subsequently, a look-up table was extracted from the SCS TR55 report from 1986 based on the empirical equations that incorporate land use and soil type according to the SCS curve number method. Detailed steps on the creation of the CN map are presented in Jabri and Hessane (2020).

3.2.8 | Modified Fourier index (MFI)

This criteria map accounts for the rainfall component of the analysis. The gridded 30-year precipitation data from 1986 to 2015 was processed based on the MFI methodology (Arnoldus et al., 1980; Morgan, 2005) to obtain the MFI rainfall intensity map as given by Equation (1):

$$MRI = \sum_{1}^{12} p^2/p(\text{mm}) \quad (1)$$

where p and P are the average monthly and annual rainfall amounts, respectively over the 30 years. The resulting map values were then normalised into the MRI criteria map used in the overlay process.

3.3 | Fuzzy multi-criteria analysis and clustering classifications

The MCA technique examines selected possibilities based on a set of criteria and objectives. When applied with the aid of GIS, it can help in categorising, examining, and appropriately organising information on choice possibilities for spatial planning (Zabihi et al., 2019). The AHP and its variant—FAHP are two of the most widely applied MCA techniques. For instance, a study by Mardani et al. (2016) notes that about a quarter of all MCA related studies in transportation systems analysis are AHP-based. A more detailed theoretical background on the AHP and FAHP as applied in this study are documented in Putra et al. (2018) and Saaty (1990). In this study, the six essential steps (Saaty, 1980) which include—“the problem definition, AHP hierarchy development, creation of the pair-wise comparison table, estimation of relative weights, consistency evaluation and the creation of the overall rating table” were taken. The classes for the flood-prone area criteria, their ratings, and relative importance are presented in Table 1. The final stage of the MCA process involves carrying out a weighted overlay of the criteria maps according to the pair-wise comparison on ArcGIS. The relative weights of the criteria and criteria ratios based on expert knowledge analysis outlined in Papaioannou et al. (2015), as applied in this study are presented in Table 2. According to the study, an expert survey was done and experts from the field of hydrology were selected to appraise the relative degree of importance of each criterion against the other in a pair-wise manner

TABLE 1 Flood prone area criteria, their classes, and ratings

Criteria	Class	Rating
DEM (m above sea level)	58 to 126.8	5
	126.8 to 195.6	4
	195.6 to 264.4	3
	264.4 to 333.2	2
	333.2 to 402	1
Slope	68.497 to 85.621	5
	51.377 to 68.497	4
	34.257 to 51.377	3
	17.137 to 34.257	2
	0 to 17.137	1
Aspect	South (S)	5
	Southwest (SW) & southeast (SE)	4
	West (W) & East (E)	3
	Northwest (NW) & northeast (NE)	2
	North	1
Flow accumulation	604,547.6 to 1,243,223	5
	326,650.7 to 604,547.6	4
	160,887.9 to 326,650.7	3
	34,127.7 to 169,887.9	2
	0 to 34, 127.7	1
HOFD (metres)	260.6 to 325	5
	196.2 to 260.6	4
	131.8 to 196.2	3
	67.4 to 131.8	2
	3 to 67.4	1
VOFD (metres)	146.51 to 200.79	5
	92.23 to 146.51	4
	37.95 to 92.23	3
	16.33 to 37.95	2
	−70.62 to 16.33	1
Topographic position index (TPI)	20.7 to 34.40	5
	7.0 to 20.7	4
	−6.70 to 7.0	3
	−20.4 to −6.70	2
	−34.1 to −20.4	1
Wetness index (WI)	17.15 to 20.53	5
	13.77 to 17.15	4
	10.39 to 13.77	3
	7.01 to 10.39	2
	3.63 to 7.01	1
Curve number (CN)	91.6 to 100	5
	83.2 to 91.6	4
	74.8 to 83.2	3
	66.4 to 77.8	2
	58 to 66.4	1

(Continues)

TABLE 1 (Continued)

Criteria	Class	Rating
Modified Fourier index (MRI)-mm	111.9 to 113.6	5
	110.2 to 111.9	4
	108.5 to 110.2	3
	106.8 to 108.5	2
	105.1 to 106.8	1

(Papaioannou et al., 2015). Figure 3 highlights the 10 criteria maps that constituted the criteria for the flood-prone area mapping in their normalised forms.

The final flood-prone area vulnerability maps were validated using historical records of flooding in the study area and different data classification/clustering methods were further applied at the end in defining the vulnerability classes of the potential flood-prone areas. Classification-clustering techniques used for creating the ranges of the vulnerability classes are highly pivotal in the accuracy of any given vulnerability map. The available classification methods on ArcGIS geostatistical analyst environment include; the natural breaks (Jenks), manual interval, defined interval, equal interval, quantiles, and standard definition (ESRI, 2020). Each method has its uniqueness and applicability based on the nature of the data/map to be classified. For instance, Jenks method is apt in optimising the arrangement of values into separate classes and aims to maximise the variance between classes while minimising the variance within classes. On the other hand, standard deviation shows the variation of the classes from the mean values and the class breaks are created at equal ranges of values that are proportionate to the standard deviation.

Of the different data classification/clustering techniques applied iteratively, only two were found suitable—Geometrical interval and natural breaks, and the results obtained from these two clustering techniques from each multicriteria analysis are presented and compared.

The clusters obtained for each classification technique were separated into five classes ranging from 1 to 5—very low, low, moderate, high, and very high vulnerabilities.

4 | RESULTS AND DISCUSSION

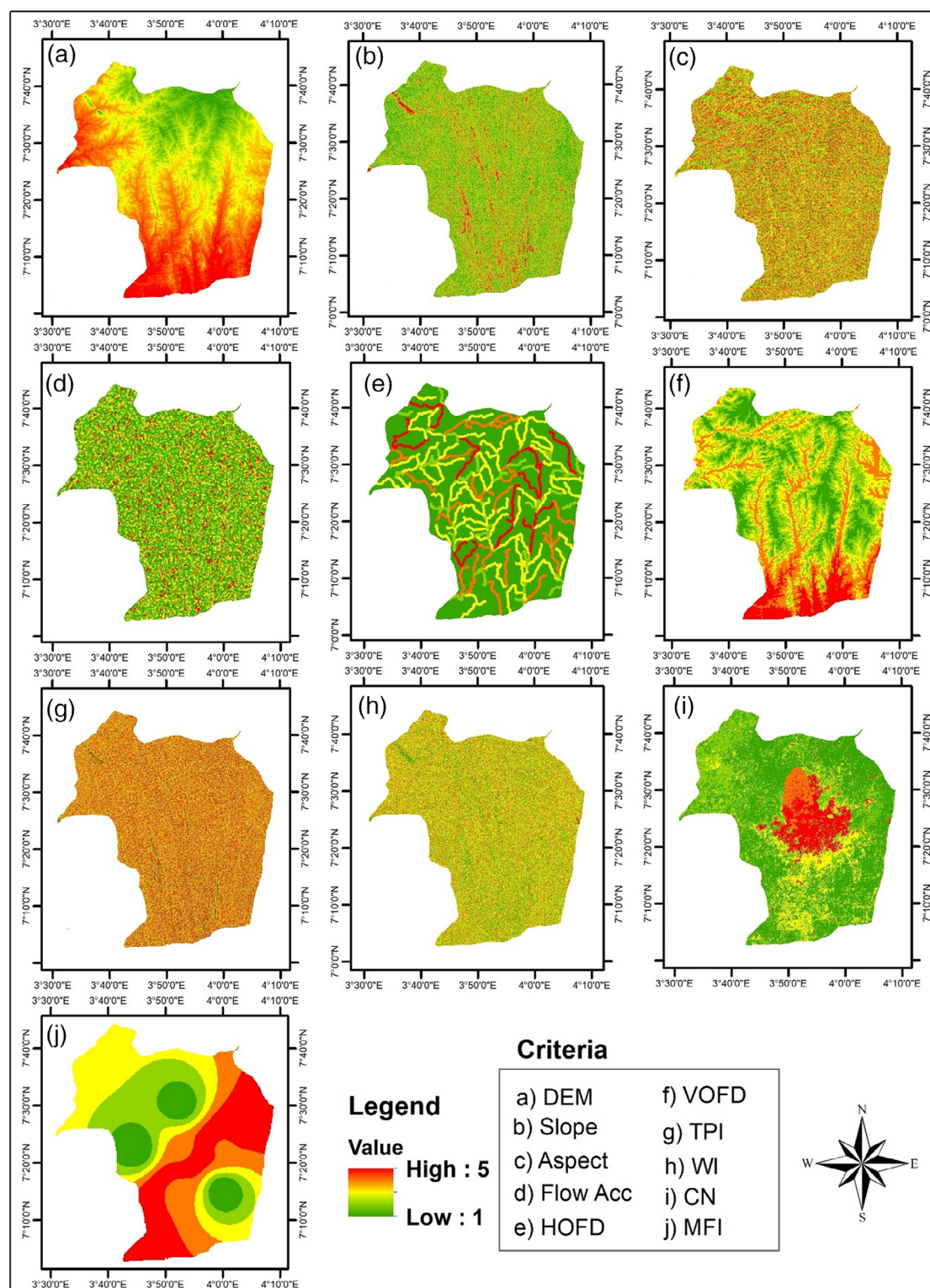
Flooding is controlled by a combination of different environmental factors which are mainly physiographic, climatic, and anthropogenic. By focusing on the 10 most important factors agreed upon by experts, this study was to develop flood vulnerability maps. The validation was done by comparing the high vulnerability areas identified in the final maps with the historical information on the flooded areas in the most recent state-wide flooding in 2011 which were also highlighted in previous studies (Agbola et al., 2012; Ajayi et al., 2012; Eguaroje et al., 2015). Figure 4 represents the four final prone area maps differentiated by the MCA and clustering techniques used.

The resultant vulnerability classes in percentages based on the two clustering techniques were used—natural breaks (Jenks) and

TABLE 2 Criteria weights and consistency ratios based on expert knowledge (Papaioannou et al., 2015)

	DEM	Slope	Aspect	Flow acc.	HOFD	VOFD	TPI	WI	CN	MFI	CR
AHP	0.03	0.11	0.02	0.15	0.08	0.07	0.08	0.26	0.17	0.03	4.3%
FAHP	0.00	0.13	0.00	0.19	0.05	0.03	0.06	0.32	0.22	0.00	6.8%

Abbreviations: CR, consistency ratios.

**FIGURE 3** The flood-prone area criteria maps showing their normalised spatial distributions

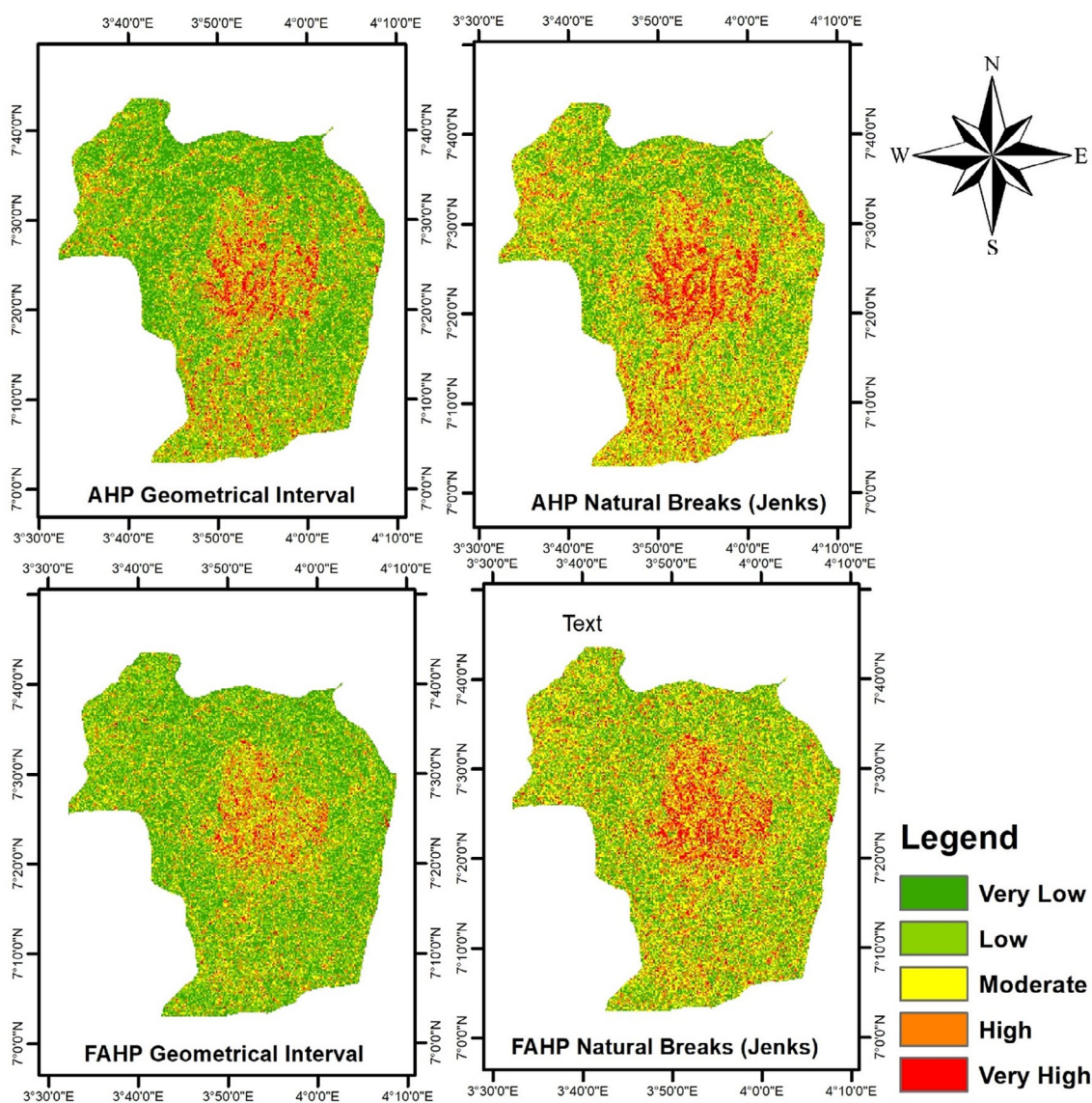


FIGURE 4 The final flood-prone vulnerability maps for Ibadan, Nigeria

TABLE 3 The percentages coverage of each vulnerability class in the flood-prone area maps

Flood prone area classes (%)				
Vulnerability cluster types	AHP		FAHP	
	Natural break	Geometrical interval	Natural break	Geometrical interval
Very low	19	31	18	30
Low	29	38	27	37
Moderate	27	16	28	14
High	18	12	20	15
Very high	7	3	7	4

geometric interval, are presented in Table 3. Overall, Table 3 revealed that there is not much difference between the natural breaks and geometrical interval clustering techniques. For instance, over 50% of the study area falls under the low and moderate vulnerability classes in

both clusters. However, natural breaks consistently showed relatively higher “very high” prone areas (7% against 3% for AHP and 7% against 4% for FAHP) and a relatively lower “very low” prone area (19% against 31% for AHP and 18% against 30% for FAHP).

TABLE 4 The percentages coverage of each vulnerability class in the flood-prone area maps

Flood prone area classes (km ²)				
Vulnerability cluster types	AHP		FAHP	
	Natural break	Geometrical interval	Natural break	Geometrical interval
Very low	555	935	588	959
Low	850	1129	906	1175
Moderate	864	437	837	495
High	603	446	545	376
Very high	208	133	204	75

In Figure 4, it was observed that the “very high” flood-prone areas are concentrated at the centres of the images. These areas coincide with the urban local government areas (LGAs)—Ibadan North, Ibadan Northeast, Ibadan Northwest, Ibadan Southeast, Ibadan Southwest and the semi-urban LGAs of the study area such as the southern parts of Akinyele, south-eastern Egbeda and Lagelu, northern Oluyole, north-western Ona-ara and the south-western parts of Ido LGAs.

For planning purposes, Table 4 represents the vulnerability classes of the areas in terms of km² which shows that the combined “high” and “very high” flood-prone areas are 811 km² (natural break), 579 km² (Geometric Interval), 749 km² (natural break), and 451 km² (Geometric Interval), respectively for the AHP and FAHP clusters. Hence, areas totalling 451 to 811 km² of land are highly or very highly prone to floods in the Ibadan. Conservatively, at least 451 km² (approx. 15%) are highly or very highly prone to flood and these areas are mainly concentrated in the urban and semi-urban regions of the study area.

These findings are in tandem with the few previous related studies where flood vulnerability mapping was wholly or partially covered in parts of or the entire study area. The study by Eguaroje et al. (2015) where the weighted linear combination technique was applied reported that about 56% of the study area falls under the slightly vulnerable class. Similarly, another study that only focused on the urban LGAs of the study area showed that the bulk of the built-up areas are highly susceptible to flash floods (Adefisan et al., 2015). However, no quantitative information on the areas affected was given in the study. The previous studies attributed flood vulnerability to urbanisation (Adefisan et al., 2015; Ajayi et al., 2012) and from this study, there seems to be a direct correlation between urbanisation and flood susceptibility as the flood-prone areas are mainly concentrated in the urban regions of the study area.

5 | CONCLUSION

Flood risk mapping involves determining the amount and extent of flooding and its impact on land cover areas. The GIS-based MCA techniques were applied in the mapping of flood-prone areas in Ibadan, Oyo state Nigeria. The two MCA techniques applied namely AHP and the FAHP are based on the relative weights of flood vulnerability criteria and consistency ratios which are then weighted

with the aid of GIS. The final vulnerability maps were grouped into five categories using the natural breaks and geometrical interval clustering techniques. The five categories ranging from very low to very high representing the least to the most probable areas prone to flooding. The findings of the study revealed that over 50% of the study area falls under low and moderate vulnerability classes. The “very high” prone areas are mainly concentrated in the urban local government areas namely; Ibadan North, Ibadan Northeast, Ibadan Northwest, Ibadan Southeast, Ibadan Southwest and some parts of the semi-urban LGAs. In the two clustering techniques used, natural breaks consistently showed relatively higher “very high” prone areas (7% against 3% for AHP and 7% against 4% for FAHP) and a relatively lower “very low” prone area (19% against 31% for AHP and 18% against 30% for FAHP). Finally, at least 451 km² of the 3080 km² study area are “highly” or “very highly” prone to flood. The information provided by the study can act as guides to policymakers and environmental conservation specialists for flood risk management and mitigation, and sustainable land-use planning and potential.

DATA AVAILABILITY STATEMENT

Data available on request from the authors.

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