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Research Article

Flood Susceptibility Assessment of Lagos State, Nigeria using Geographical Information System (GIS)-based Frequency Ratio Model

Ibrahim Opeyemi Isiaka[1*], Suara Gafar[1], Sodiq Abayomi Ajadi[2], Ibrahim Olarewaju Mukaila[3], Kingsley Odinakachukwu Ndukwe[1], Suebat Oluwakemi Mustapha[4]

[1] Department of Surveying & Geoinformatics, School of Environmental Technology, Federal University of Technology, Akure, NIGERIA
[2] ITECH Energy Company, Portharcourt, NIGERIA
[3] Balad Geotechniks Global Impacts Limited, Ibadan, NIGERIA
[4] Department of Fisheries & Aquaculture, School of Agriculture & Agricultural Technology, Federal University of Technology, Akure, NIGERIA

* Corresponding author: I. O. Isiaka
E-mail: isiakaibroheem@gmail.com

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Abstract

Flood is a common disaster affecting the lives and properties of humans. It has a history of causing great damage to infrastructure; disrupt transportation, also, a greater degree of flooding can lead to caving in of the earth causing landslides. Oftentimes, Lagos state, the economic capital of Nigeria has been subjected to flooding owing to heavy rainfall coupled with other causative factors. This study aims to prepare a flood susceptibility map of Lagos state using the frequency ratio model and Geographic Information System (GIS). In this paper, we have considered ten salient contributing factors to flooding, they are; slope, curvature, drainage proximity, drainage density, soil type, average annual rainfall, topographic wetness index, land use & land cover, normalized difference vegetation index, and elevation to delineate the area susceptible to flooding. The flood inventory map was prepared from 100 flood points identified from news reports, and Google Earth Imagery and was further divided into 70 for training and 30 for testing the model. The result shows that 12.54% and 11.62% of the total area of Lagos state have very high and very low levels of flood susceptibility, respectively. The Area Under the Curve (AUC) has been used to validate the model and was found to perform satisfactorily with a success rate of 64% and a prediction rate of 61%. This work is a necessary input for mitigating flood hazards in the state and will serve a good purpose in making decisions for city planners and the government.

Keywords: AUC, Flood Susceptibility Map, Frequency Ratio, GIS, Lagos

Introduction

Floods are the most common and destructive natural disasters that affect human health and natural environments (Zou, et al., 2013; Samanta, et al., 2018). Flood Susceptibility Assessment mapping is a very important tool needed to hinder the continuous events of the flood, which aids in reducing the adverse effects of flood hazards. Although it is impossible to prevent the occurrence of floods, it is possible to predict these catastrophic events, and to some extent, control those using appropriate methods and analyses (Cloke and Pappenberger, 2009; Farina et al., 2018; Moazzam et al., 2018; Menteş et al., 2019; Ozulu et al., 2021). Also, the necessary measures to prevent floods and mitigate their adverse effects seem inevitable (Huang et al., 2008; Dang et al., 2011; Alvarado-Aguilar et al., 2012), one of which is undoubtedly the development of flood susceptibility maps (Bubeck et al., 2012; Direk et al., 2012).

It frequently occurs in the Lagos part of Nigeria, especially during the rainy season. They have been past studies on flood susceptibility mapping of Lagos state. The D-infinity algorithm and Digital Elevation Model (DEM) derived dataset was used to delineate flood-prone areas and surface runoff modeling in Lagos state (Odumosu et al., 2014). Idowu and Zhou 2021 studied the flood risk mapping of Lagos state by combining the Analytical Hierarchy Process AHP and Shannon entropy weighting techniques (Adesina et al., 2022). Also, The HEC-RAS and HEC-HMS have been used for 3D modeling of flooding in Lagos Island Local government area of Lagos state by Adewara. et al. 2018. However, they haven't been any research that employed a frequency ratio model for flood susceptibility mapping of the study area.

The frequency ratio model is one of the bivariate statistical techniques used to assess risk in flood mapping (Debabrata and Prolay 2019). It is a simple, cheap, and unique method in that it assigns individual weights for each class. For delineating flood susceptibility areas, the frequency ratio model and geographic information system are applied to determine the likelihood of flood and generate the flood susceptibility map respectively (Youssef et al., 2015; Anucharn and Iamchuen, 2017; Samanta et al., 2018). This study adopted the frequency ratio model technique as it has proved very satisfactory from past studies in flood susceptibility mapping in India, Pakistan, Thailand, Bangladesh, and Korea (Moung-Jin et al.

2012; Kamonchat et al. 2019; Razavi-Termeh. and Sadeghi-Niaraki 2019; Debabrata and Prolay 2019; Sangeeta and Ninganagouda 2021; Awais et al. 2022; Kamilia and Rodeano 2022).

This study aims to generate the flood susceptibility map of Lagos state using the Frequency Ratio model. Furthermore, the Area under the Curve (AUC) will be used to assess the accuracy and efficiency of this model.
Lagos is surrounded by several freshwater streams, a lagoon, and the Atlantic Ocean. The city of Lagos is a known to be a low lying city with a flat topography which have majority of its area at or below sea level, with an elevation of 1.5 meter above sea level on average (Ajibade, 2017). According to Ikuemonisan and Ozebo, 2020, the city is at a sinking rate of close to ~87mm per year, which means that the water bodies is increasingly infringing at the city's edge. Water is trapped and quickly builds up following heavy rainfall or storms due to low elevation and sinking land, as well as massive drainage problems caused by waste-clogged drainage systems (Adeloye and Rabee, 2011). This megacity is vulnerable to coastal flooding, which will be exacerbated by rising sea levels (Odunuga et al., 2014; Kaoje and Ishiaku, 2017; Obiefuna et al., 2021) due to its geographical location, relatively flat topography, and an average elevation of only 1.5 m above sea level (Ajibade et al., 2016). The most recent IPCC report projects a 54-cm sea level rise for the Lagos region by 2100 under the RCP4.5 scenario and a 75-cm rise under the RCP8.5 scenario (IPCC, 2022). Regional sea level rise in Lagos is combined with widespread subsidence (land sinking) caused primarily by groundwater extraction and urbanization, with subsidence rates ranging from 2 to 87 mm per year across the city and revealed to be the highest in coastal areas and other areas where heavy buildings are placed on landfills (Ikuemonisan and Ozebo, 2020). The combined effects of subsidence and sea level rise in the Lagos suggest that a 2°C increase in global warming as a result of climatic and anthropogenic factors could result in a relative sea level rise of more than 90 cm in Lagos by 2100 (Jevrejeva et al., 2016; Bamber et al., 2019; Johnson, 2021). Lagos State, home to over 15 million persons, have witnessed a constant increase in the demand for houses which have caused people to encroach forests and wetland for raising structures resulting in the recurring flood which threatens the economic strength of this state and its infrastructures prompting the necessity to delineate flood-prone areas; consequently, justifying this research work.

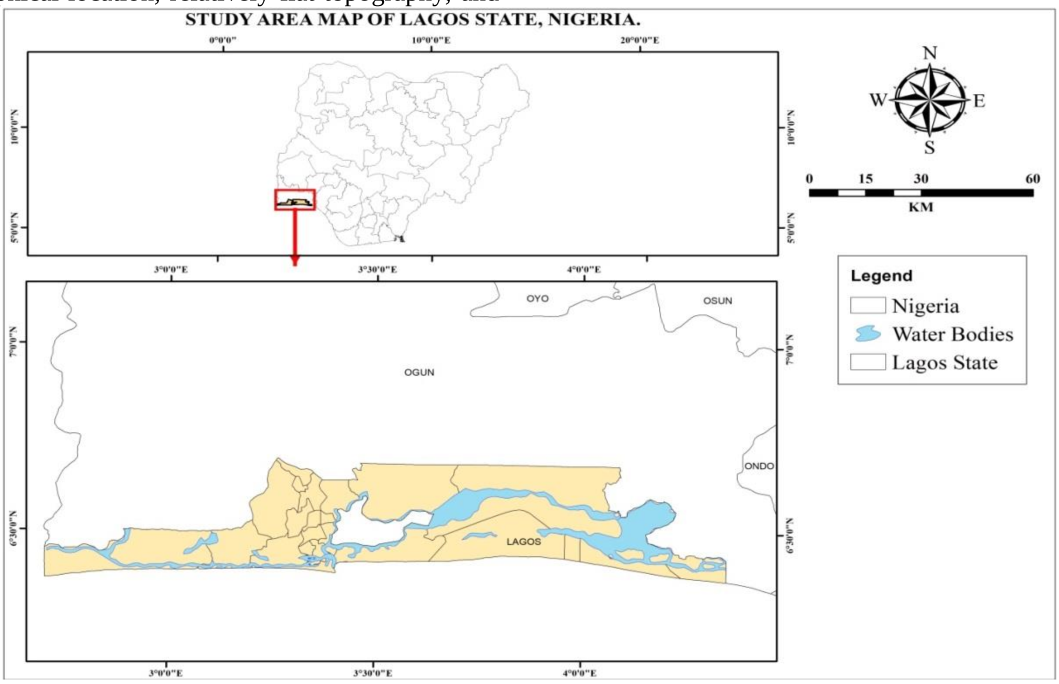

Fig. 1. The map of Lagos state.

Materials and Method
Study Area

This research covers Lagos state, the smallest and one of the most populated states in Nigeria, lying between latitudes 6°0'0"N to 7°0'0"N and longitudes 2°0'0"E to 6°0'0"E along the coastline of the Atlantic Ocean (Fig. 1). It is located in the southwestern part of Nigeria and is made up of 20 local government areas with state capital being Ikeja. It is the state with the highest economy, as a result, it is seen as the economic and financial capital of Nigeria, housing many businesses both small-scale and larger ones. The state receives an average rainfall of between 880mm and 890mm yearly, this, together with its proximity to the Atlantic Ocean oftentimes results in flooding causing significant damage to the lives and properties of the inhabitants of the state.

Flood Inventory Map

Identifying previous flood locations is very pertinent in delineating potential flood areas (Kamilia and Rodeano 2022). The performance of a model is largely dependent on the data sets used for training the model as well as validating the model (Hassan et al., 2021). In this paper, published News reports of previous flood events from

2001 to 2022 and Google Earth Imagery Historical map mode have been leveraged to identify the location of these points (Fig. 2). The total of 100 points was identified within the study area and these points were divided into training data and testing data. 70% of the flood points have been used to train the model while 30% were used to validate the flood susceptibility model. There is no definite rule on how the data should be divided but it has been seen in (Hassan et al., 2021).

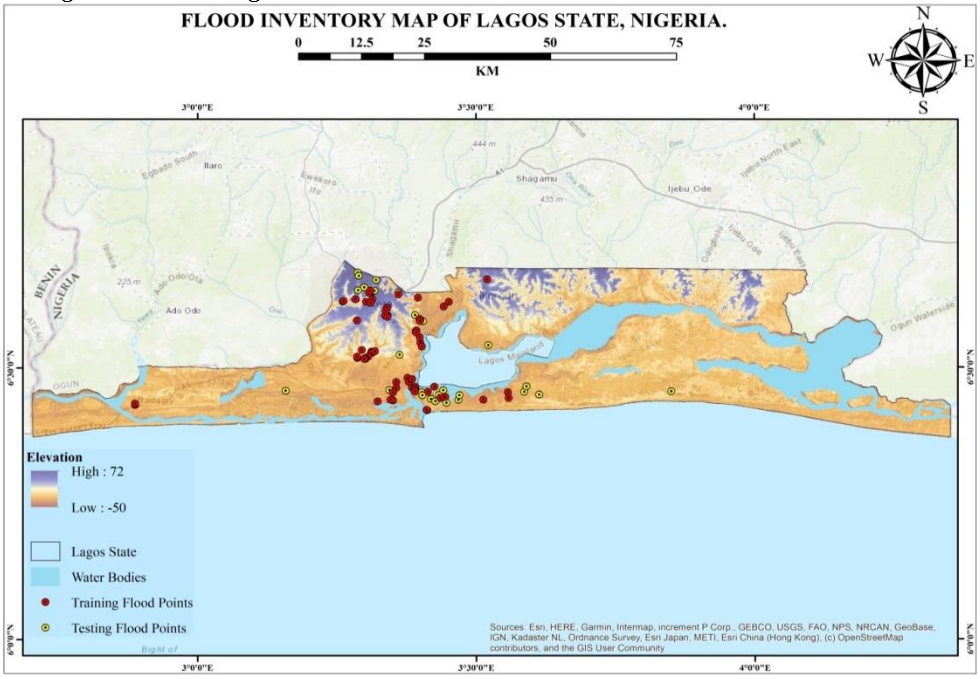

Fig. 2. Flood inventory map of Lagos state.

Table 1. Datasets and their sources

S/N	Data	Resolution	Format	Sources	Derived Maps
1	DEM	30m	Raster	https://urs.earthdata.nasa.gov	Slope, Drainage density, Elevation, Drainage proximity, Curvature, TWI
2	Landsat 8 Imagery (2020)	30m	Raster	https://earthexplorer.usgs.gov	Land use & Land cover map, NDVI
3	Soil Data	-	Vector	https://www.fao.org	Soil Map
4	Rainfall data (2001-2020)	-	Vector	https://crudata.uea.ac.uk	Average Annual Rainfall map
5	Flood points	-	vector	News reports and Google Earth imagery	Flood inventory map

Flood Conditioning Factors

It is very crucial to identify the individual factors that influence flood occurrence in an area to get reliable outcomes. Although flood-causing factors may vary based on the catchment [Debabrata and Prolay, 2019], this study has considered some conditioning factors based on past research (Razavi and Sadeghi 2019). Ten parameters have been considered in this study, they are; elevation, slope, rainfall, soil type, drainage proximity, topographic wetness index (TWI), land use and land cover (LULC), drainage density, curvature, and normalized difference vegetation index (NDVI) Table 1. Derivative factors and topographic data play a significant role in determining flood susceptibility and vulnerability (Munir et al., 2022). ArcGIS 10.7.1 and ArcGIS Pro 1.2 were used for all the geoprocessing operations with all vector data being converted to a raster of resolution of 30m. Table 1 shows the dataset and its sources.

Elevation data of Lagos state ranges from -50 to 72m above sea level. It is common knowledge that water will flow from a higher elevation and accumulates at a lower elevation. Therefore, areas with lower elevations have higher chances of being affected by rainfall making them more flood-prone than areas with higher elevations. The elevation data was classified into < -25.6, -25.6 to -1.2, -1.2 to 23.2, 23.2 to 47.6 and > 47.6 as shown in Fig 3a. The slope map shown in Fig 3b, has been classified as <10°, 10°-20°, 20°-30°, 30°-40° & >40°. It controls the surface runoff, vertical infiltration process, and rate of soil erosion (Debabrata and Prolay, 2019) of a region. Rainfall data describes the amount of water that falls to the ground surface during a certain period. Severe flooding is mostly caused by atmospheric conditions that lead to heavy rainfall. According to research, heavy rainfall is the major cause of flash flooding due to the increase in the pressure on the soil's pores. Average annual rainfall has been prepared from 2001 to 2020 and it has been classified into <889mm, 889-890mm, 890-891mm, 891-893mm & >893mm Fig 3c. Soil type Fig

3d has some characteristics that influence flood occurrence such as its porosity, and moisture content. Soils like sandy soil that drains water quickly, clay soil on the other hand doesn't. This means that the presence of clay soil increases the possibility of flood occurrence more than in areas with sandy soil. The soil type map has been classified into Sandy-Loam, Clay, Loam & Sandy-Loam-Clay. Drainage proximity is a measure of the distance from the existing water body within the study area. Fig 3e shows that the drainage proximity has been classified into <2000m, 2000-4000m, 4000-6000m, 6000-8000m, and >8000m. Topographic Wetness Index (TWI) shows the amount of flow accumulation at any point in a drainage basin and the ability of the water to travel downslope with gravity (Cao et al., 2016). It is used to describe and give value to the hydrological processes controlled by the topography of an area. The TWI was calculated using Eq. 1.

$$TWI = ln\left(\frac{A_S}{\tan b}\right) \qquad \textbf{(Eq.1)}$$

Where A_S is the specific catchment area, and b (radian) is the slope gradient.

The TWI of Lagos state is shown in Fig f. The LULC is also one of the main variables in flood mapping as it reflects the current use of land, its pattern, and types of its use and hence its importance to soil stability and infiltration (Waqas et al., 2021). LULC map was generated using the supervised classification method and has been classified into forest, built-up, bare lands, vegetation, and water bodies as shown in Fig 3g. Drainage density Fig 3h is the total length per unit area of the river network. Flood susceptibility is directly proportional to the drainage density. Curvature influences the amount of surface runoff and infiltration (Cao et al., 2016). Flat areas accumulate water easily. Curvature was classified into Concave (curvature equals –ve), Convex (curvature equals +ve) and Flat (curvature equals 0) Fig 3i. NDVI was used to observe the response of vegetative cover to visible and near-infrared sunlight. Its values range from -1 to +1 and it was classified into four. The NDVI was obtained by using different bands from Landsat 8 imagery. Eq. 2 was used to determine the NDVI. Fig 3j shows the NDVI.

$$NDVI = \frac{Band\ 5 - Band\ 4}{Band\ 5 + Band\ 4} \qquad \textbf{(Eq.2)}$$

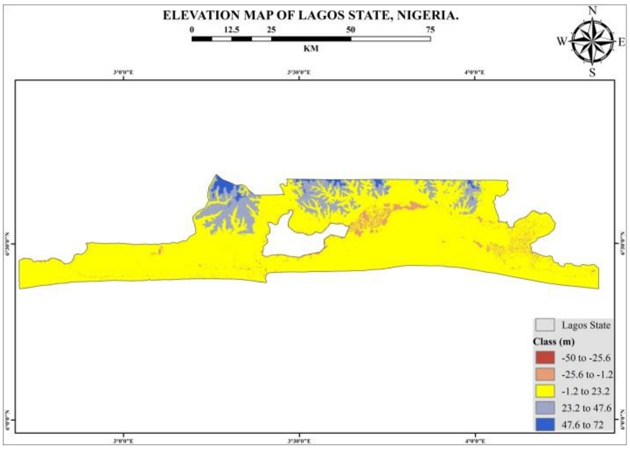

Fig. 3a. Elevation.

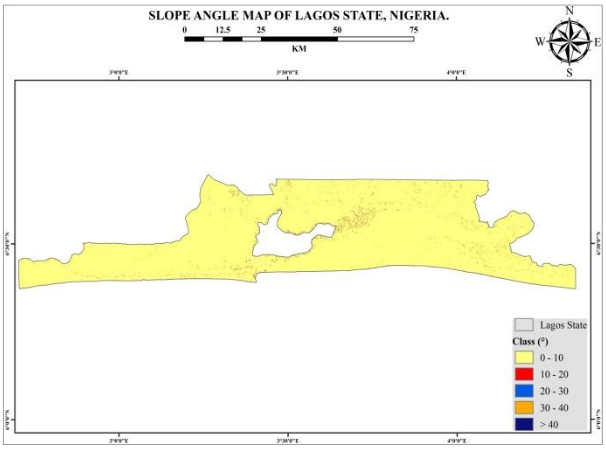

Fig. 3b. Slope map

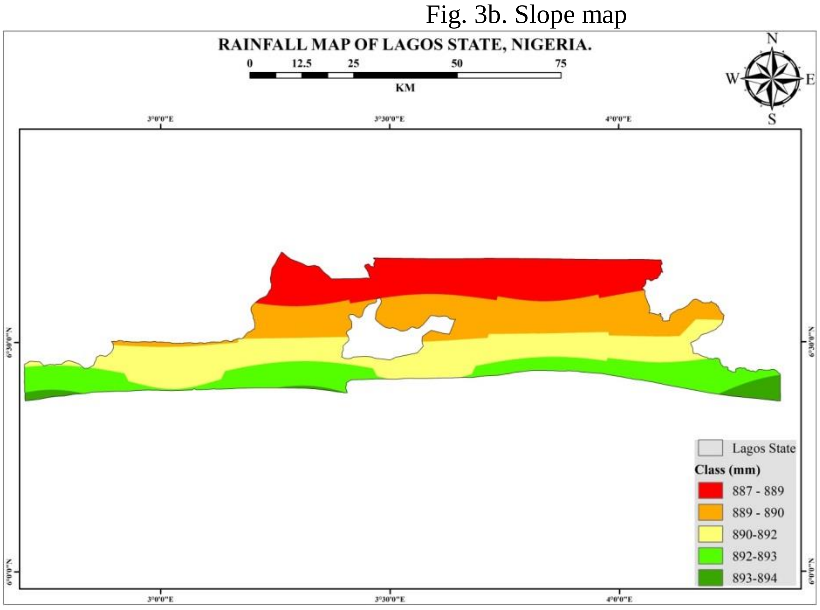

Fig. 3c. Annual average rainfall map.

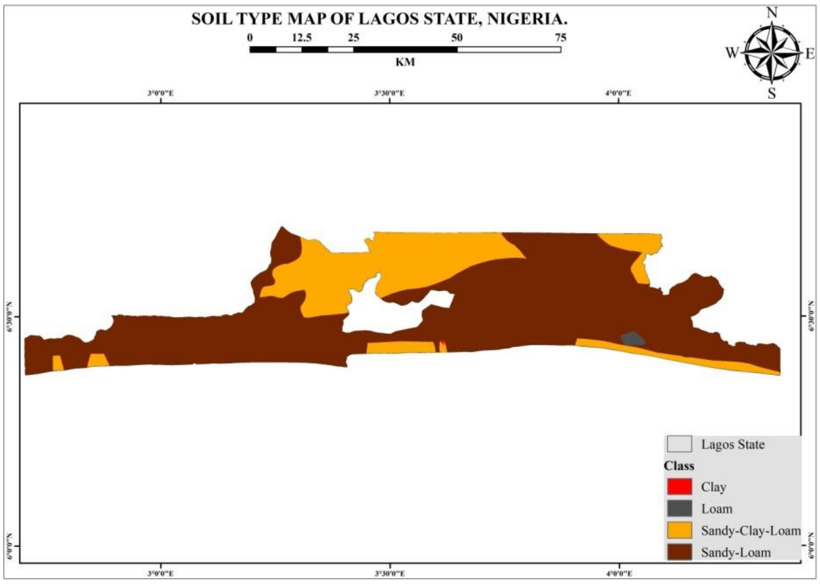

Fig.3d. Soil type map.

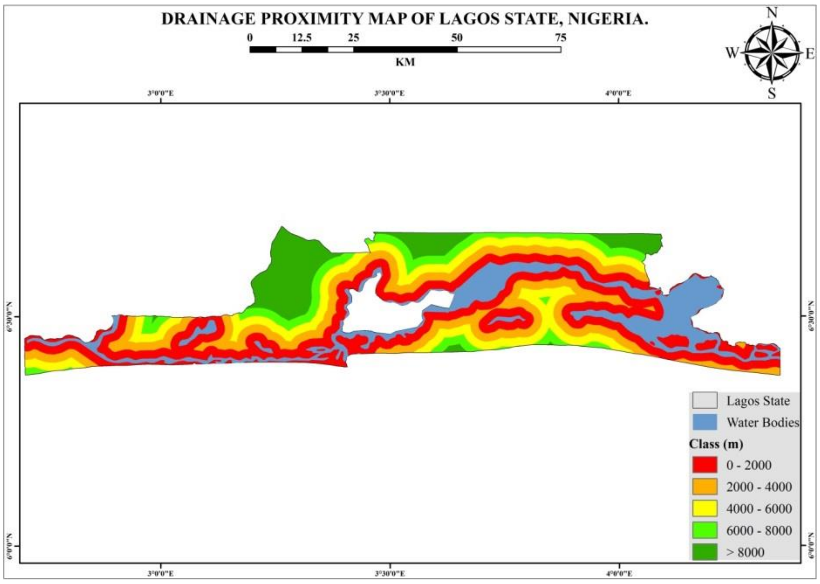

Fig. 3e. Drainage proximity map.

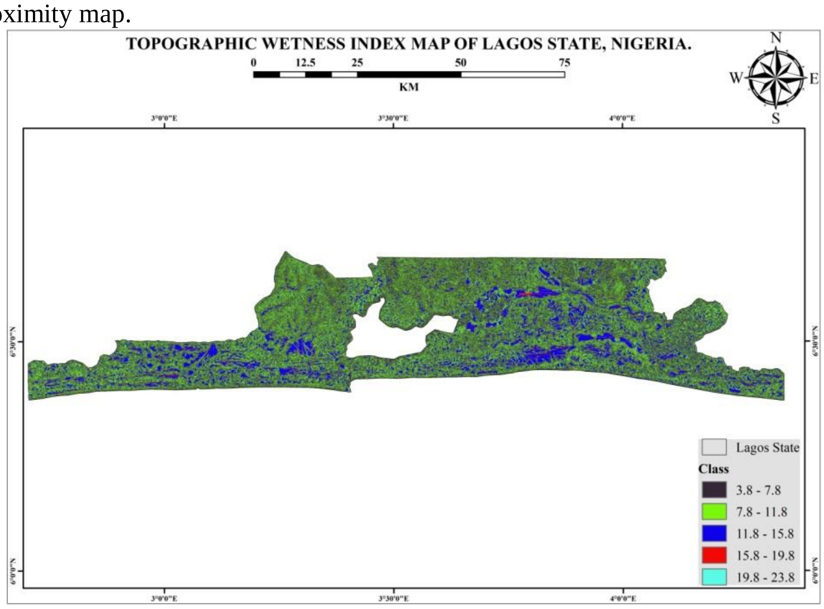

Fig. 3f. Topographic wetness index map.

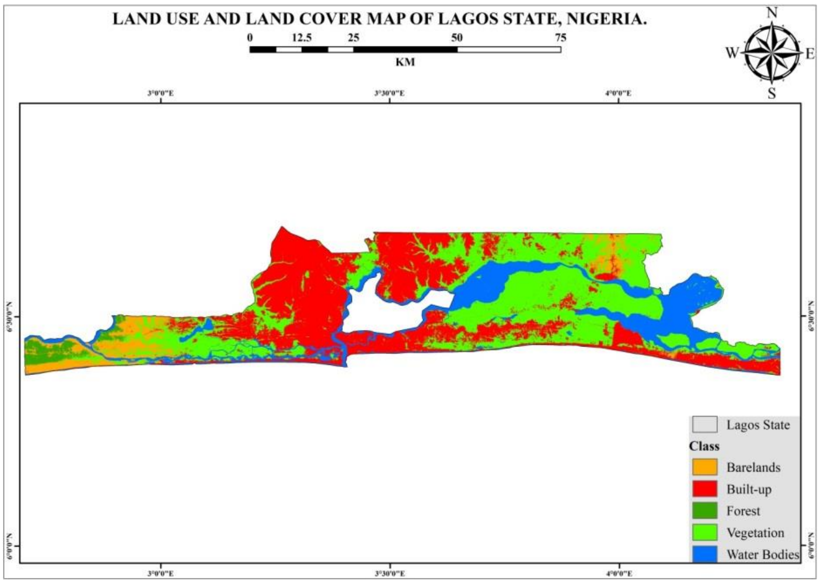

Fig. 3g. Land use/land cover map.

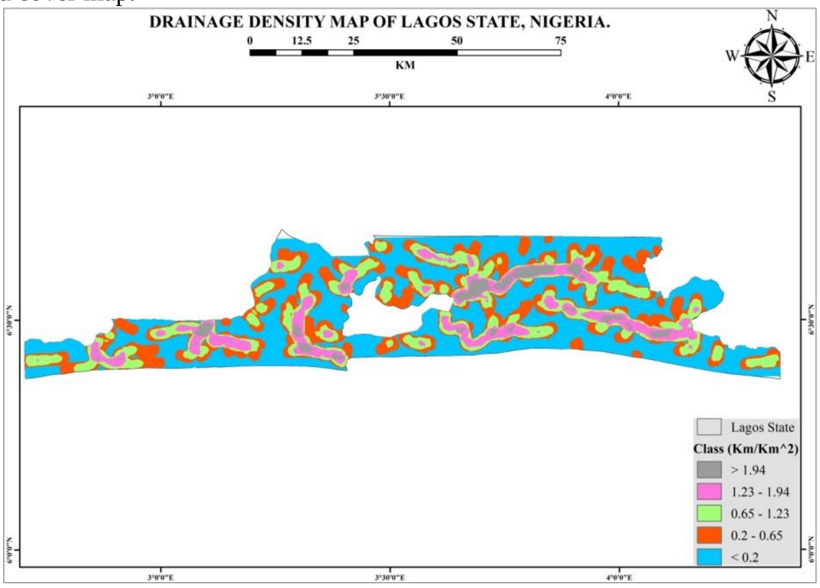

Fig. 3h. Drainage density map.

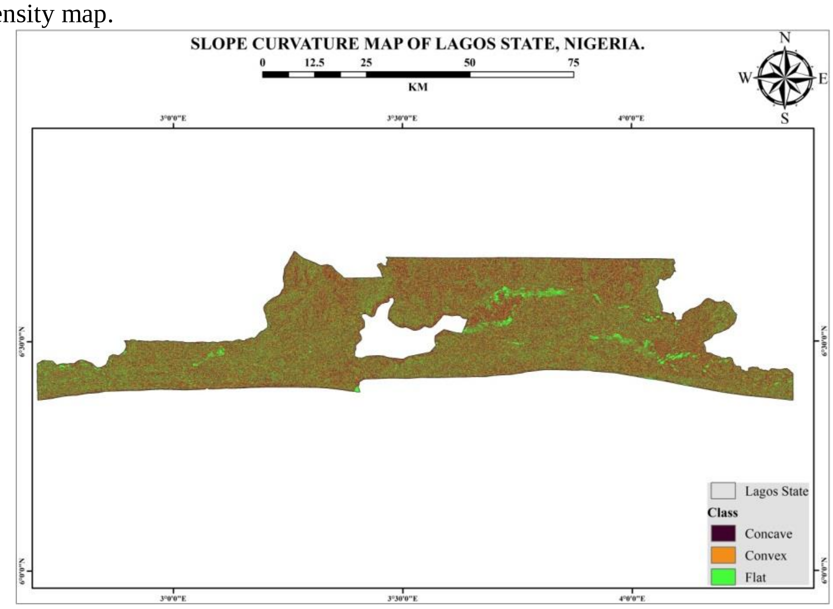

Fig. 3i. Curvature map.

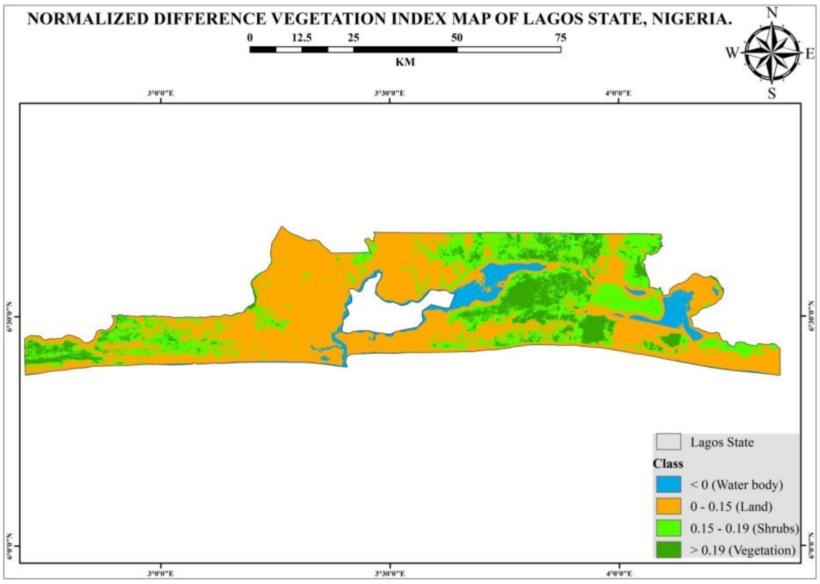

Fig. 3j. NDVI map.

Frequency Ratio Model

To develop a model that will accurately delineate areas susceptible to flooding it is very important to study the relationship between the previous flood locations and identified causative factors. The frequency ratio, FR is an observation-based probabilistic approach that shows how the past events (in this case flood occurrence) within a certain area are associated with the causative factors. This method has been used to delineate areas that are susceptible to landslides and it has been used to prepare groundwater susceptible map [Razavi and Sadeghi 2019], also, in preparing flood risk maps (Moung-Jin et al., 2012 & Sangeeta and Ninganangouda 2021). It is a very simple technique for observing the relationship between the causative factors of a flood and the previous flood events. The training data which makes up 70% of the flood points was used to build the frequency ratio model while the remaining 30% were used to test and validate the model.

FR values were calculated for all the classes of the ten causative factors and this method have proven very useful for the consideration it places on assigning values to individual class with Eq. (3). If the FR value is greater than 1, it shows the factor has a close association with flood occurrence while if FR is less than 1, it shows that the factor has a low relationship with flood occurrence. The individual FR values of the classes were normalized to within the values of 0 and 1 to determine the relative frequency, RF using Eq. (4). This will help to minimize the model from overfitting or under fitting. Eq. (5) was used to compute the prediction rate and PR of the flood causative factors as a way of solving the problem of down siding from the assigned RF. This led to the assignment of a final weight for all the factors. The final flood susceptibility index was created by adding up the product of the prediction rate and relative frequency.
Finally, the final flood susceptibility was determined using Eq. (6) where all the calculations were carried out using the Microsoft Excel package while ArcGIS software was used to perform all the geoprocessing operations leading to the development of the final flood susceptibility map which was further classified into five which includes; very low, low, moderate, high and very high.

$$FR = \frac{\%\, Pixel\ of\ the\ factor's\ class\ within\ the\ study\ area}{\%\, Number\ of\ flood\ points\ within\ the\ factor's\ class} \quad \textbf{(3)}$$

$$RF = \frac{FR_{ij}}{\sum_{i=1}^{m} FR_{ij}} \quad \textbf{(4)}$$

$$PR = \frac{(RF_{max} - RF_{min})}{(RF_{max} - RF_{min})_{min}} \quad \textbf{(5)}$$

$$FSI = \sum (PR * RF) \quad \textbf{(6)}$$

Where:

FR_{ij} = Frequency ratio of the class

m = number of classes for a factor

$(RF_{max} - RF_{min})$ = Difference between the maximum RF and the minimum RF

$(RF_{max} - RF_{min})_{min}$ = Minimum value of the difference between the maximum and minimum RF

The frequency ratio model was validated using the area under the curve, the AUC score. Here, the 70 flood points have been used to determine the training AUC score while the remaining 30 flood points were used to validate the model producing the testing AUC score. AUC score ranges between 0 and 1 [Sangeeta and Ninganangouda 2021], where a model is valued as efficient if it has an AUC score greater than 0.5 but if the score is less than 0.5 it is deemed unsatisfactory [Kamonchat et al., 2019 & Sangeeta and Ninganangouda 2021].

Result and Discussion

The different independent factors that result in flooding are crucial in flood analysis. The result of the selected parameters that influence flooding is shown in table 2. Slope class 0-10° has a 98.6% pixel domain with the highest FR value of 0.99 among the other slope classes according to the analysis of FR for the association between flood site and slope angle. It implies that lower slope angles area experiences a greater percentage of floods in the study area as a result of the effects of high slope zones. The area has a lower slope is more exposed to flooding (Liuzzo et al., 2019). The FR Analysis in the case of curvature indicated concave class with the highest FR value (1.15), followed by convex (0.94) and flat (0.91). However, flooding frequently occurred in areas having flat curvature (Tehrany et al., 2017).

Khosravi et al., (2016) stated that NDVI has a negative relationship with flooding. It implies that the presences of vegetation prevent flooding. The FR analysis of the NDVI shows water bodies with the highest FR value of 4.62 followed by land (0.57), shrubs, and vegetation with 0 values. The various sizes of water bodies in Lagos make the state naturally susceptible to flooding. The study area is dominant in sandy loam soil. It has a 73.84% pixel domain. Sandy-clay-loam has a 25.56% pixel domain, followed by loam and clay with pixel domain values of 0.43 and 0.17, respectively. Fine-grained soils dominated by clay have low infiltration rates due to their smaller-sized pore spaces (Prachansri, 2007), which resulted in rapid runoff during heavy rainfall. Sandy loam soil has the highest FR value (0.31) with sandy-clay-loam second to it (0.12).

Drainage proximity is an important factor in flood susceptibility mapping. Drainage proximity was divided into five classes. The classes 2000 – 4000m and 4000 – 6000m have the highest and lowest probability of flooding with FR values of 1.51 and 0.00 respectively. The higher likelihood of flooding is strongly linked to higher drainage density as it points toward a greater surface runoff (Das, 2019). Drainage density was divided into five classes, at first, the FR values decrease as the drainage density increased which later change the trend at the highest drainage density class. The highest density class (> 1.94) indicated the highest value of FR (2.29).

Table 2. Frequency ratio analysis

Factors	**Class**	**Pixel of Domain**	**% Pixel of Domain**	**No Flood Events**	**% Flood Events**	**FR**	**RF**
Slope	0° – 10°	3812236	98.60	70	100	0.99	1.00
	10° – 20°	39566	1.02	0	0	0	0
	20° – 30°	5860	0.15	0	0	0	0
	30° – 40°	4415	0.11	0	0	0	0
	> 40°	4326	0.11	0	0	0	0
Curvature	Concave	1457492	37.70	23	32.86	1.15	0.38
	Flat	956458	24.74	19	27.14	0.91	0.30
	Convex	1452453	37.57	28	40.00	0.94	0.31
NDVI	< 0 (water body)	255179	6.60	1	1.43	4.62	0.89
	0 - 0.15 (land)	2176943	56.30	69	98.57	0.57	0.11
	0.15 - 0.19 (shrubs)	958194	24.78	0	0	0	0
	> 0.19 (vegetation)	476087	12.31	0	0	0	0
Soil Type	Sandy-Clay-Loam	988090	25.56	33	47.14	0.54	0.12
	Clay	6525	0.17	0	0	0	0

	Sandy-Loam	2854977	73.84	37	52.86	1.40	0.31
	Loam	16811	0.43	0	0	0	0
Drainage proximity	0 - 2000	1803678	46.65	30	42.86	1.09	0.25
	2000 - 4000	751377	19.43	9	12.86	1.51	0.35
	4000 - 6000	542874	14.04	0	0	0	0
	6000 - 8000	317202	8.20	4	5.71	1.44	0.33
	> 8000	451272	11.67	27	38.57	0.30	0.07
Drainage density	< 0.2	1790197	46.30	17	24.29	1.91	0.31
	0.2 - 0.65	905014	23.41	19	27.14	0.86	0.14
	0.65 - 1.23	670604	17.34	15	21.43	0.81	0.13
	1.23 - 1.94	374355	9.68	18	25.71	0.38	0.06
	> 1.94	126233	3.26	1	1.43	2.29	0.37
Land use & Land cover	Water Bodies	659556	17.06	0	0	0	0
	Built-up	1395509	36.09	65	92.86	0.39	0.03
	Vegetation	1490383	38.55	3	4.29	8.99	0.78
	Forest	76197	1.97	0	0	0	0
	Bare lands	244758	6.33	2	2.86	2.22	0.19
Topographic Wetness Index (TWI)	3.8 - 7.8	1280116	33.11	24	34.29	0.97	0.23
	7.8 - 11.8	1567737	40.55	32	45.71	0.89	0.21
	11.8 - 15.8	919149	23.77	10	14.29	1.66	0.39
	15.8 - 19.8	85513	2.21	3	4.29	0.52	0.12
	19.8 - 23.8	13888	0.36	1	1.43	0.25	0.06
Elevation	-50 to -25.6	527	0.01	0	0	0	0

	-25.6 to -1.2	150626	3.90	0	0	0	0
	-1.2 to 23.2	3245665	83.95	53	75.71	1.11	0.71
	23.2 to 47.6	419800	10.86	17	24.29	0.45	0.29
	47.6 to 72	49785	1.29	0	0	0	0
Average Annual Rainfall	887 – 889	930449	24.06	21	30.00	0.80	0.19
	889 – 890	986336	25.51	21	30.00	0.85	0.20
	890-892	1109759	28.70	19	27.14	1.06	0.25
	892-893	746266	19.30	9	12.86	1.50	0.36
	893-894	93593	2.42	0	0	0.00	0

The Wetland of Lagos continuously underwent sand filling and conversion for housing units which impacted the ability of the natural systems to prevent the severity and frequency of flooding. Urban areas increase runoff due to extensive impervious soil and fallow farmland increases runoff where there is no vegetation cover to control and prevent the rapid flow of water to the soil surface (Ullah & Zang, 2020). However, FR outputs indicated a weak relationship exists between LULC and flooding in the study area. Vegetation, bared land, built-up, water bodies, and forest have FR values of 8.99, 2.22, 0.39, 0.00, and 0.00, respectively.

TWI has a direct positive relationship with flooding (Khosravi et al. 2016). RF values for the TWI classes of 11.8 – 15.8 and 3.8 – 7.8 were estimated as the highest at 1.66 and 0.97, respectively. The FR analysis in the case of elevation results indicates that the middle and penultimate classes of -1.2 to 23.2 and 23.2 to 47.6m were the only important classes on flooding with an RF value of 1.11 and 0.45, respectively. The other classes of elevations have no importance on flooding in the study area. Rainfall is one of the most important parameters in flood generation. The FR values of rainfall classes show a positive correlation between rainfall and flooding in the study area. Class 892 – 893 has the highest FR value of 1.50 followed by 890 – 892, 889 -890, and 887 – 889 with values of 1.06, 0.85, and 0.80, respectively. Various previous studies have established a positive correlation between rainfall and flooding (Sahana & Patel, 2019; Das, 2019).

The final flood susceptibility map of Lagos State was divided into five classes; very low, low, moderate, high, and very high levels of susceptibility. Fig. 4 shows that majority of the areas susceptible to flooding in Lagos state are areas lying relatively close to the water bodies and are mostly characterized by low elevation. Table 2 shows that 12.54% (436272.3Km^2) and 28.91% (1006050.6Km^2) of the total area of Lagos State amount to areas having very high and high susceptibility levels of flood respectively. These areas coincide with part of the Epe, Ibeju-Lekki, Amuwo-Odofin, Ojo, and Kosofe Local government areas. 11.62% (404465.4Km^2) and 21.94% (763539.3Km^2) amount to areas with a very low and low level of flood susceptibility while 24.99% (869435.1Km^2) are the areas with a moderate level of susceptibility. The extent of satisfaction of this map and model has been tested and validated using the Area Under the Curve metric.

Validation of model

It is necessary to perform validation for the flood susceptibility map developed. According to Sahana et al. 2019, it was reported that the accuracy of the flood susceptibility map developed by the Frequency Ratio (FR) model is evaluated by the receiver operating characteristics (ROC) curve. Area Under Curve (AUC) is one of the common indices of the ROC curve which is used to interpret the accuracy of the model (Krzaowki and Hand 2009). Jaafari et al. 2014 defined AUC as the quality of models by showing the model's capacity to predict an occurrence and non-occurrence of the event. The AUC values vary from 0.5 – 1 for an ideal model. When the AUC value is 1, it indicates the highest level of accuracy for the susceptibility map provided, and if the model cannot predict the flood occurrence better than the probability, then the AUC value is less than or equal to 0.5. Zhu & Wang 2009, highlights the correlation below the curve for AUC values and estimation assessment is as follows (0.9 – 1, excellent, 0.9 – 0.8, very good, 0.8 – 0.7, good, 0.6 – 0.7, satisfactory, 0.5 –

0.6, Poor). The success rate for final flood susceptibility validated using the Area Under Curve approach was 0.64 (64%) and the prediction rate was 0.61 (61%). The AUC curve showed that the model performed satisfactorily, with a success and prediction rate of 0.64 and 0.61, respectively.

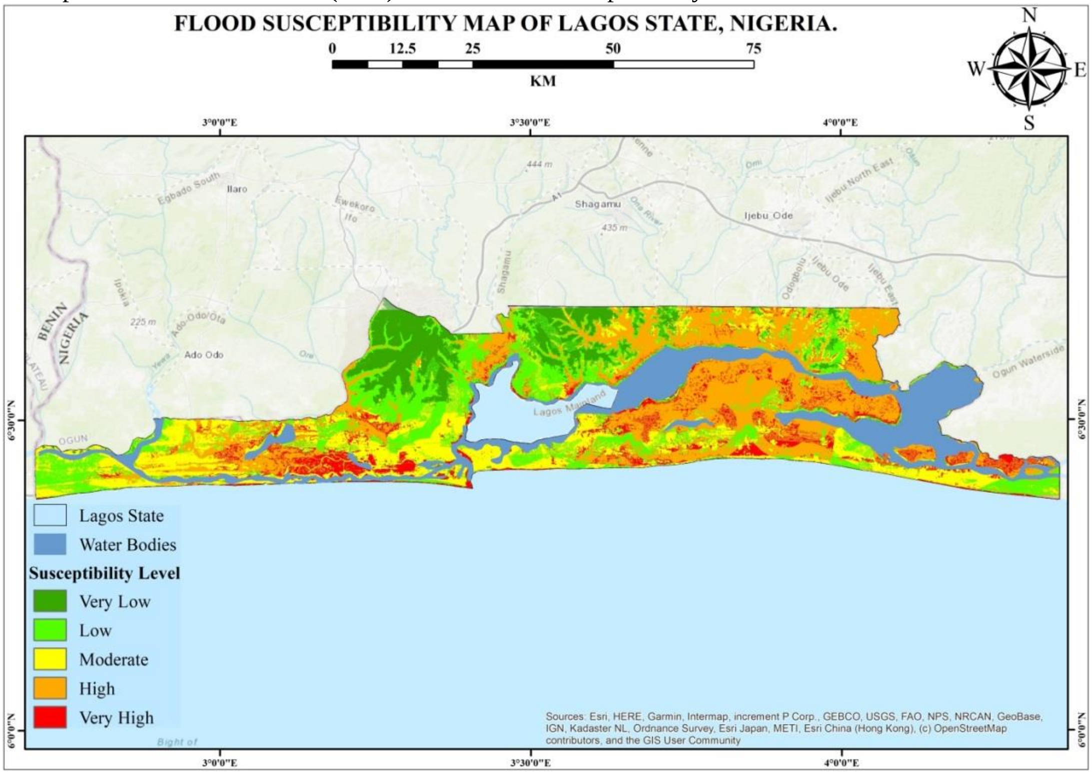

Fig. 4. Flood Susceptibility map

Table 3. Spatial distribution of Flood susceptibility map in the study area

Susceptibility Class	Area in Km^2	Percentage (%)
Very low	404465.4	11.62
Low	763539.3	21.94
Moderate	869435.1	24.99
High	1006050.6	28.91
Very high	436272.3	12.54

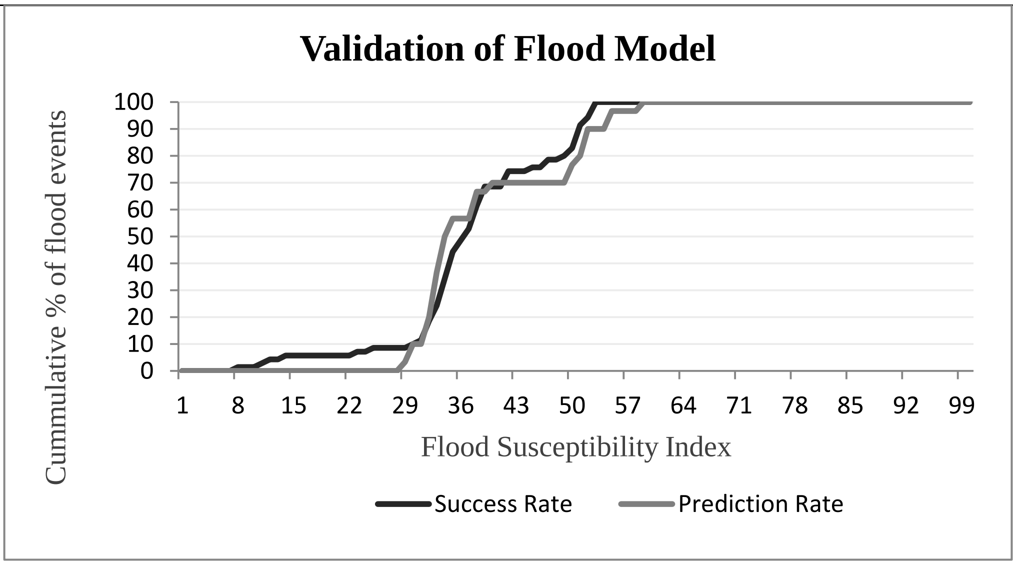

Fig. 5. Validation of the flood susceptibility model of Lagos state

Conclusion

Flood is unarguably one of the serious causative agents of serious damage to infrastructure, transportation, earthquakes, and at times landslides. This study was used to create a flood susceptibility map of Lagos state using the frequency ratio model. The training datasets consisted of 70 flood points while the validation datasets consisted of 30 flood points. Ten salient contributing factors were used to delineate the areas that are susceptible to flooding. The result of the study shows that approximately 12.54% of parts of Lagos state have very high flood susceptibility while 11.62% are prone to very low levels of flood susceptibility. The Area Under the Curve was used to validate the model adopted for the study and was found to perform satisfactorily with a success rate of 0.64 and a prediction rate of 0.61. The comparison of the efficiency of this model with previous studies shows that the model can be a key component of an early warning system for flood hazards. The approach utilized in this study can be implemented in other areas where various factors can be taken into account, depending on the availability of data.

This study serves as a key contributor to mitigating flood hazards and will greatly help in deciding for appropriate planning of areas in the state by the government

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