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# Assessment of flood vulnerability in Osun River Basin using AHP method

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## Abstract

Flooding is a global natural disaster that occurs when water rises over normal levels and damages infrastructure, buildings, and land. Lately, a substantial rise has occurred in the frequency and severity of floods in Nigeria due to urbanization, population growth and climate change. This study aims to identify areas in the Osun River Basin (ORB) in southwest Nigeria that are at risk of flooding as a result of increased rainfall patterns that can induce river flooding. 10 flood factors contributing to flood susceptibility were obtained around the study area. These remote sensing data were analyzed using a weighted overlay on ArcGIS. The Analytic Hierarchy Process (AHP) was particularly applied in analysing the flood factors and creating the flood susceptibility maps. Results obtained showed that flood events are probable in areas along the river bank, some areas that are low-lying terrains and areas where there is high rainfall. Ogun State falls within the areas with the lowest digital elevation, therefore the state is very highly susceptible to flooding from the tributaries of the Osun River. Areas such as Ijebu North, Ijebu North East, Ijebu East and Ijebu Ode were identified as highly susceptible to flooding from the maps created. This study will further help stakeholders and policymakers in reducing the impact of flooding in these areas.


**Keywords** Flooding, Osun River Basin, ArcGIS, Flood susceptibility, Flood factors, Climate change, Analytic Hierarchy Process (AHP)

## Background

Flooding is an event where water upsurges higher than standard levels and causes harm to land, structures, and infrastructure [26]. Recent years have seen a sharp rise in disasters caused by the climate. Variations in geological conditions, population growth and use of land all have an impact on climate-related disasters [9]. Floods are the deadliest of all climate-related natural catastrophes, killing an estimated 80% of people worldwide and causing an estimated $US60 billion in annual losses in addition to harming infrastructure and agricultural land already in use [21]. Scientists predict that sea levels will rise by 4 inches by 2030 due to changes in the climate, which could potentially result in catastrophic flooding in many regions of the world [44]. According to a study conducted by the Institute of Environmental Studies, the effects of the rise in sea level will put over sixty per cent of global communities in danger of inundation thirty years from now [43].

In Nigeria, floods have become more frequent and severe in recent years, causing significant harm to infrastructure, socioeconomic systems, and human lives. Destruction of agricultural land and infrastructure worth millions of dollars is caused each year by floods [21]. According to the Center for Research on the Epidemiology of Disasters (CRED), flooding between 1969 and 2020 resulted in approximately 21,000 fatalities and losses

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totalling US$17 billion [21]. The International Federation of the Red Cross and Red Crescent Society (IFRC) also brought attention to the September 2020 flood, which affected 192,594 people across 22 states and resulted in 825 injuries, 155 fatalities, and 24,134 displaced people [21]. The Federal government reported that 1.3 million people were relocated from their villages and at least 603 people died in floods during the flooding that hit Nigeria in 2022. About 31 states experienced flooding in 2022, with Anambra, Kogi, Delta, Kebbi, Jigawa and Bayelsa among the states where flood-related fatalities have been reported [30]. According to the Federal Ministry of Humanitarian Affairs, Disaster Management, and Social Development, 82,053 homes were destroyed, 2,504,095 million people were impacted, and 332, 327 hectares of land were utterly destroyed. According to other figures, there were 2,407 injuries, 121,318 partially destroyed homes, and 108,392 partially ruined acres of agriculture [30]. A cholera outbreak in northeastern Nigeria that was brought on by flooding that polluted the water supply has claimed at least 64 lives [14]. According to the United Nations World Food Programme and Food and Agricultural Organization, Nigeria is highly vulnerable to devastating levels of starvation [10]. Also, according to the UN Office for Humanitarian in Nigeria, fourteen million kids and nineteen million adults are in danger of malnutrition. In the north and northeast of the nation, 400,000 kids are vulnerable to severe acute starvation, and 500,000 more are in the states of Katsina, Zamfara, and Sokoto in the northwest [41].

Mapping flood susceptibility is essential to evaluate flood risk locations and create flood mitigation strategies [42]. An efficient method that is essential to the creation of a flood risk mitigation strategy is utilizing a composite risk and vulnerability rating to assess the likelihood of flooding. Several studies have been conducted regarding river basins' susceptibility to flooding. Ramkar and Yadav [35] produced a map of data-scare river basins with an assessment of flood danger. The datasets used were analysed based on the Analytical Hierarchical Process (AHP) with Geographic Information System (GIS). The study's flood hazard map was created with seven flood variables in consideration, and a map of flood danger was used to locate the river basin's high-risk areas [35]. Kumar and Jha [23] also created a flood risk map using 7 flood factors with GIS tools. The study divided the basin's territory into several risk zones, with huge portions of India's Purnia and Madhepura being under high risk. Adedoja et al. [3] analyzed the flood-prone zones in Osogbo, Osun state, Southwest Nigeria's Okoko basin. In the study, four flood factors were investigated. The flood-vulnerable areas of Osogbo's Okoko basin were mapped for this study. According to the study, the estimated area of the study area is 17.85 km2, of which 14.2 km2 is in the locations that are most susceptible and 3.6 km2 is in the less susceptible regions. Meanwhile, 8204 buildings were identified to be highly susceptible to flood disasters. A map of flood-prone areas of the city of Akure South, Nigeria, was also produced by another study [36]. According to the study's results on flood vulnerability, the high vulnerability zone took up 25.5% of the area of study, while the extreme area of great danger made up 13.9%. Of the research region, the low vulnerability zone made up 23.8% and the intermediate vulnerability zone 36.8%.

A study additionally identified areas in Owerri, Imo State, Nigeria's Otamiri River Basin that were vulnerable to flooding. The study produced a flood vulnerability map that highlighted the study area's sensitive areas and the criteria for assessing flood risk within it [48]. AHP was used for identifying high-risk areas for flooding using seven factors. Extremely high flood vulnerability, which can be exceedingly dangerous, was found in the study. While existing research provides valuable insights into some causes and consequences of flood vulnerability, gaps in knowledge warrant further investigation. From previous research, the Analytic Hierarchy Process (AHP) is an effective tool for assessing flood vulnerability. The Analytic Hierarchy Process (AHP) is a decision-making method used in remote sensing and geographic information science to organize and analyze complex decisions [1]. It combines mathematics and psychology to compare several options and assign each criterion an importance weight based on pairwise comparisons. An extensive and methodical framework for decision-making is offered by AHP, which divides complicated issues into smaller, more manageable components. This is especially helpful in determining flood vulnerability, which takes into account a variety of variables including hydrological, geological, socioeconomic, and environmental aspects [17]. AHP facilitates prioritizing the various elements that affect a region's susceptibility to flooding. AHP enables identifying the most crucial areas that require attention in flood risk management by allocating weights to each criterion according to their respective importance [32]. Flood vulnerability assessment is a difficult process that considers several flood-causing factors, each of which affects the total risk of flooding differently. The application of the Analytic Hierarchy Process (AHP) enables the methodical examination of these many components, ensuring that all pertinent factors are taken into account during the evaluation. AHP makes it feasible to rank the factors according to how important they are in relation to the danger of flooding. This is especially important in the Osun River Basin, where the distinct geographical, meteorological, and socioeconomic features of the area may mean that certain influences have differing degrees of impact. The identified research gap is that flood vulnerability has not been carried out on the Osun River Basin using the AHP method. Given this, this research focused on assessing the flood vulnerability of the Osun River Basin using AHP. This study showed the Osun River's influence and impact on areas in its tributaries, which has not been investigated in previous research. Furthermore, this study focused on identifying areas that are vulnerable to flooding in the Osun River basin (ORB) as the study area and created a flood risk map which can be used to prioritize the mitigation effects.

## Flooding in Osun River Basin

Flooding poses a serious threat to the environment in Nigeria, especially in the Osun River Basin. It affects both human populations and the environment, with a variety of causes and effects [29]. Floods' changing characteristics are mostly due to factors like urbanization and global climate change. As a result, flood events are now occurring more frequently and covering a wider range of areas globally [33]. In the Osun River Basin, annual flood events have resulted in substantial loss of life and property damage [27]. In recent years, the capital of Osun state, Osogbo, has suffered from devastating floods primarily caused by heavy rainfall [22]. For instance, in 2013, the Oke Bale and Gbonmi areas experienced severe flooding that resulted in significant property damage [22]. Subsequent years, 2015 and 2016, also witnessed catastrophic flooding events, causing extensive havoc to both lives and properties. The well-known factor accountable for the higher incidence of flooding is the wide spatial distribution of low-lying beaches and river floodplains accompanied by constant urbanization [50]. Typically, flat terrain contains areas that are vulnerable to flooding where floods stagnate for long periods, and this causes environmental danger [28]. In general, squatter settlements and subpar buildings, increased household density, land subsidence, urbanization of flood-prone areas, changes in land use, and population growth are the main causes of increased flooding in many regions of the world [34]. The hazards associated with floodwaters are also linked to several aspects of the flood, including its depth, duration, velocity, sediment load, rate of rise, and frequency of recurrence. Flooding is a complicated problem that affects the Osun River Basin and all of Nigeria. It is influenced by a number of variables, such as urbanization, climate change, and inadequate waste management. The economy, social well-being, and environment of the impacted communities are all impacted by the extensive implications.

There were hundreds of homeless individuals and many destroyed buildings in Osogbo in 2019 after areas that had never experienced flooding before were swamped for many days [6]. Similarly, other regions within Osun state, including Ikirun, Ede, Ilobu, and Ifon, have also grappled with ongoing flooding issues [40]. Adeoye et al. [5] investigated flood incidents in Nigeria and the risks they posed. This study focused on the socioeconomic effects of flooding in Nigerian cities and emphasized that climate change is a significant factor [5]. Adelekan [4] examined Lagos' urban coastal populations' susceptibility and offered insights into similar susceptibilities in the Osun River Basin. Umar and Gray [47] surveyed flood mapping and modelling in Nigeria in regard to the frequency and impact of floods in the last decade. The study examined the frequency and patterns of flooding and approaches to its modelling in relation to current practices globally. It was observed that the northern part of Nigeria is affected more by flooding than the south [47]. To enable appropriate planning and provide long-term solutions to the regular harm that flooding does to people and their properties in Osogbo, the capital of Osun state, Alimi et al. [6] mapped out flood-vulnerable locations inside Osogbo Metropolis using the geospatial methodologies. The Analytic Hierarchy Process (AHP) was utilized in this study to combine eight (8) flood-causing factors. According to the study, roughly 24% of the entire research area is located in a high flood risk zone, whereas 21% and 55% are located in a moderate or low flood risk zone, respectively. The correctness of the Analytic Hierarchy Process (AHP) which is the methodology was demonstrated by a strong correlation between the studied area's flood-prone areas and past flood occurrences. This motivated this research, considering that Osogbo is just a small part of the Osun River Basin, this research aimed to apply the same methodology to the Osun River Basin to identify areas that are most vulnerable to flooding.

## Study area: Osun River Basin (ORB)

The Osun River is a major river in southwestern Nigeria that overflows during the rainy season. The areas in the tributaries are therefore vulnerable to river flooding. The Osun River basin extends along the states of Osun, Oyo, Kwara, Lagos, and Ekiti and includes the drainage basin of the Osun River and its tributaries. The Oke-Mesi Hill is the source of the Osun River's flow system, which flows north through the Itawure Gap to latitude 7°53″ [8]. From there, it passes through Osogbo and Ede before entering Lagos Lagoon, which is located about 8 km to the east of Epe [31]. The basin has a Koppen Aw-type tropical continental climate with a humid tropical rainforest climate, AW represents a Tropical savanna climate with dry-winter characteristics [8, 40]. The rainy season usually spans from April to November which is about eight months.

In the basin, two maximum rainfall events with peaks in July, September, and October are usually used to determine the rainy season [2]. Typically, the year-round maximum and nearly constant temperature is around 30 °C [2]. The length of the Osun River (ORB), which has been there for centuries, changes with the seasons. The river traverses rocks from the Basement Complex while passing through a small valley [20]. Major river systems in the basin, including the Osun, Erinle, Otin, and Ayiba Rivers, have both dams and weirs. There are weirs at Okuku, Oyan, and Inisa [20]. The Oṣun River discharges into the Lagos Lagoon in southwest Nigeria after flowing south through the core of the Yoruba region. The shape file of the Osun River showing the drainage lines and the location of ORB in Nigeria is shown in Fig. 1. The length of ORB is 267 km. ORB has its source in Ekiti state while the mouth is Lekki Lagoon. The river flows through six states namely Ekiti, Kwara, Oyo, Osun, Ogun and Lagos states.

## Methods

### Data

In this research, ten flood conditioning factors were selected as features of the ORB as of 2018: ten flood factors such as rainfall data, topographic water index (TWI), slope, drainage density, digital elevation model, soil data, distances from roads, normalized difference vegetation index (NDVI), distance from rivers, and land use land cover (LULC) data was selected as characteristics of the historical flood event. One of the most important and direct causes of floods is rainfall. It affects river basins by influencing the frequency and severity of flood events [19]. Both high-intensity and prolonged rainfall can cause flooding. TWI, a hydrological measure, integrates data on the slope and upstream contributing area to determine areas where water is expected to accumulate. considering its immediate effect on surface runoff, soil moisture, and potential waterlogging, it is essential to the assessment of

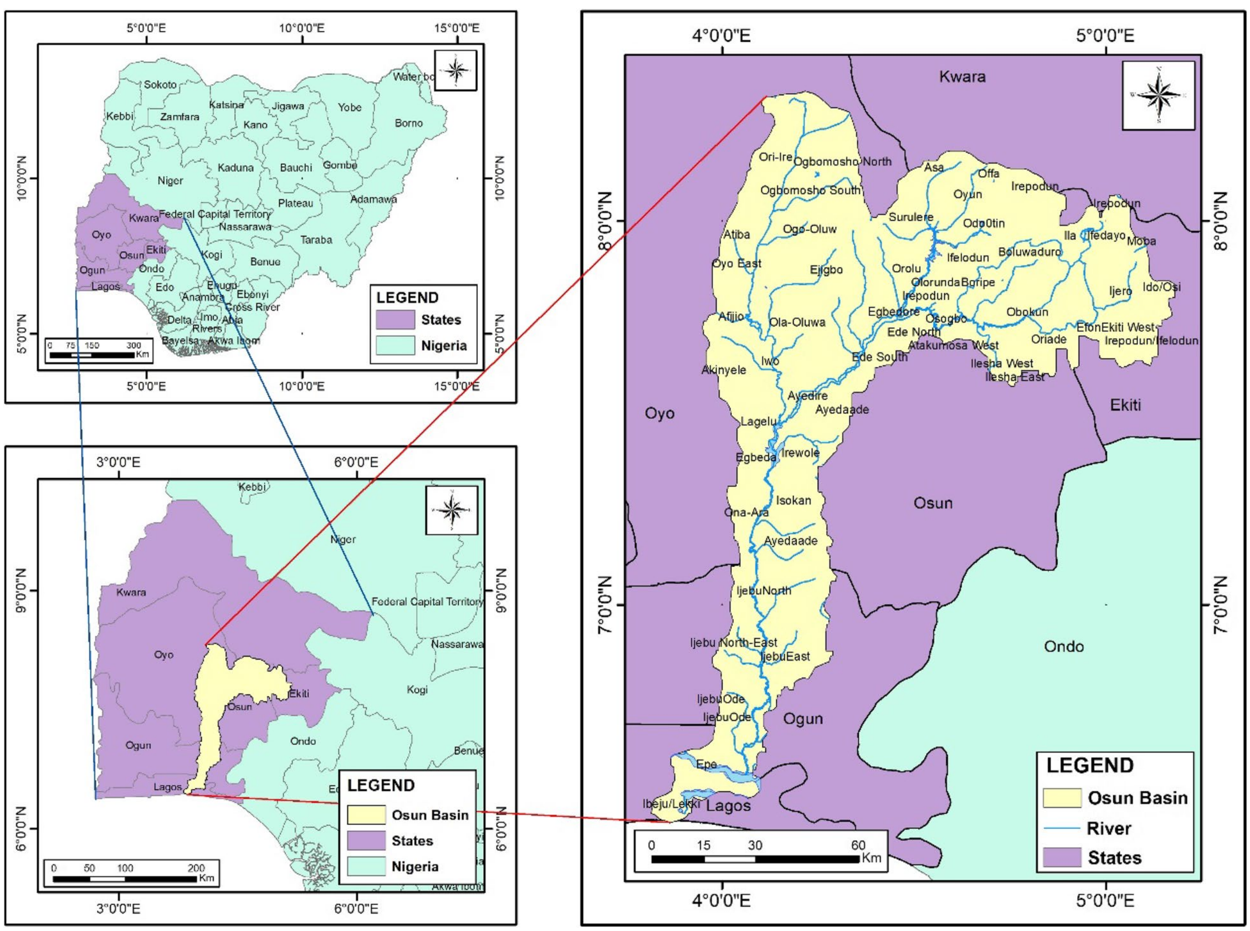


**Fig. 1** Location and Position of ORB showing Cities and Towns

flood risk [51]. Drainage density, which is the total length of streams and rivers per unit area within a watershed, is an important consideration in hydrological and flood risk assessments. It offers information on the drainage capacity of the landscape and is a crucial gauge of how rapidly and effectively water is distributed over an area. The risk of flooding may be significantly impacted by high or low drainage densities [45]. The slope is also one of the significant factors in the occurrence of floods due to its direct impact on surface runoff and infiltration potential [37]. The direct influence of slope on surface runoff and infiltration potential makes it one of the major variables contributing to the occurrence of floods. An Earth's surface representation that uses gridded elevation data is called a Digital Elevation Model (DEM). DEMs are essential for hydrological modeling and flood risk assessment because they offer comprehensive topographic data for an area. DEMs have a significant impact on flood dynamics, influencing the magnitude of floods, accumulation zones, and water flow pathways [26]. Soil type is also an important flood-causing factor, this is because the ability of different soil types to penetrate differs. For instance, clayey soils have lower penetration rates and hence higher surface runoff, while sandy soils absorb water more quickly. The ability of the soil to absorb water is further diminished by changes in land use, such as urbanization and deforestation [38]. Five different types of soil were identified, which are clay, clay loam, silt loam, loam, and loamy sand. The composition of the soil in terms of clay, silt, and sand particles is particularly important since soil features such as these have a substantial impact on flood susceptibility. Due to its fine texture, clay soil has a limited amount of pore space, which causes slow drainage and waterlogging, thereby increasing its susceptibility to flooding. Clay loam soil is more likely to flood because it contains a larger proportion of clay. Silt loam soil is less prone to flooding caused by the fact that there are more silt particles and less clay and sand particles in it. This soil also has a moderate infiltration rate and moderate drainage. Sand, silt, and clay particles make up loam soil, which offers adequate water infiltration and drainage and reduces flooding risk. Loamy sand soil is less prone to floods because it has a comparatively high sand content and a low silt and clay content. This combination produces a high infiltration rate and good drainage. Likewise, mapping the land-use-land-cover (LULC) is also a major determinant of flooding propensity, given that roads and buildings have impermeable surfaces, urbanization decreases natural infiltration, raising the danger of flooding and surface runoff [16]. Flooding is very relevant to the classification of land use and land cover. Both the frequency and severity of flooding can be dramatically impacted by changes in land cover, such as urbanization and deforestation [6, 7]. Also, there is a growing need for land for agriculture and other uses and changing land use patterns result in altered infiltration rates, which heighten the dangers associated with flood zones. Hence, flood land usage and land cover will be mapped to determine locations that are particularly susceptible to floods. Although the NDVI in and of itself does not directly affect flooding, it can provide useful data for assessing and understanding the potential risk and impact of flooding [49].

### Data sources

Rainfall data was acquired from the PERSIANN Precipitation Climate Data Record (PERSIANN-CDR), and the mean rainfall data was derived. Elevation and flooding typically have an inverse connection. In this case, the research area's elevation was taken using the digital elevation model (DEM) and then used to derive drainage lines and slopes in ORB. The digital elevation model was obtained from the Copernicus open-access hub (www.scihub.copernicus). The digital elevation model's spatial resolution is 10 m. TWI is a measure of how wet the area is and is used to identify possible floodplains in river basins. It was derived from information produced from DEM utilizing slope and flow accumulation functions. The digital elevation model, slope, Landsat satellite image, NDVI, rainfall, topographic water index (TWI), and drainage density are downloaded in raster format and analyzed using Environmental Systems Research Institute (ESRI) ArcGIS 10.8. The soil data were retrieved from the Food and Agriculture Organization (FAO), which was used to derive the water-holding capacity of the soil. The land use land cover was mapped using ArcMap version 10.8. It was utilized to determine the wetlands and is the focus of Esri's ArcGIS group of geospatial processing tools. The drainage lines were used to calculate drainage density. Likewise, land-use-land-cover (LULC) is Landsat satellite imagery which were retrieved from USGS. The Landsat satellite image was downloaded and sampled at a spatial resolution of 30 m and resampled at 15 m. The distance to the river, distance to the road and soil type are in vector format. Slope and TWI are the geomorphic factors derived from a digital elevation model. NDVI and LULC were created from the Landsat satellite image. The widely used NDVI vegetation indicator was produced using data from remote sensing, mostly satellite images. It measures how verdant and healthy the vegetation is in a certain location.

### Method of data processing with AHP

AHP is a technique in ArcGIS which is a powerful tool for making suitability maps. AHP is a structured approach, the flood-causing factors were ranked,

**Table 1** Analytic Hierarchy Process (AHP)

| Conditioning factors | | TWI | Elevation | Slope | Precipitation | LULC | NDVI | Distance from river | Distance from road | Drainage density | Soil type | Normalized principal eigenvector (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | |
| **TWI** | 1 | 1 | 1 | 1 | 1 | 3 | 5 | 1 | 3 | 1 | 1 | 13.78% |
| **Elevation** | 2 | 1 | 1 | 1 | 1 | 2 | 3 | 1 | 3 | 1 | 1 | 12.07% |
| **Slope** | 3 | 1 | 1 | 1 | 1 | 3 | 1 | 1/2 | 1 | 1 | 1 | 9.90% |
| **Precipitation** | 4 | 1 | 1 | 1 | 1 | 3 | 2 | 2 | 3 | 1 | 1 | 13.45% |
| **LULC** | 5 | 1/3 | 1/2 | 1/3 | 1/3 | 1 | 1 | 1/3 | 3 | 1 | 1 | 6.62% |
| **NDVI** | 6 | 1/5 | 1/3 | 1 | 1/2 | 1 | 1 | 1/5 | 1 | 1 | 1 | 5.87% |
| **Distance from river** | 7 | 1 | 1 | 2 | 1/2 | 3 | 5 | 1 | 3 | 1 | 1 | 14.08% |
| **Distance from road** | 8 | 1/3 | 1/3 | 1 | 1/3 | 1/3 | 1 | 1/3 | 1 | 1 | 1 | 5.59% |
| **Drainage density** | 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 9.32% |
| **Soil type** | 10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 9.32% |

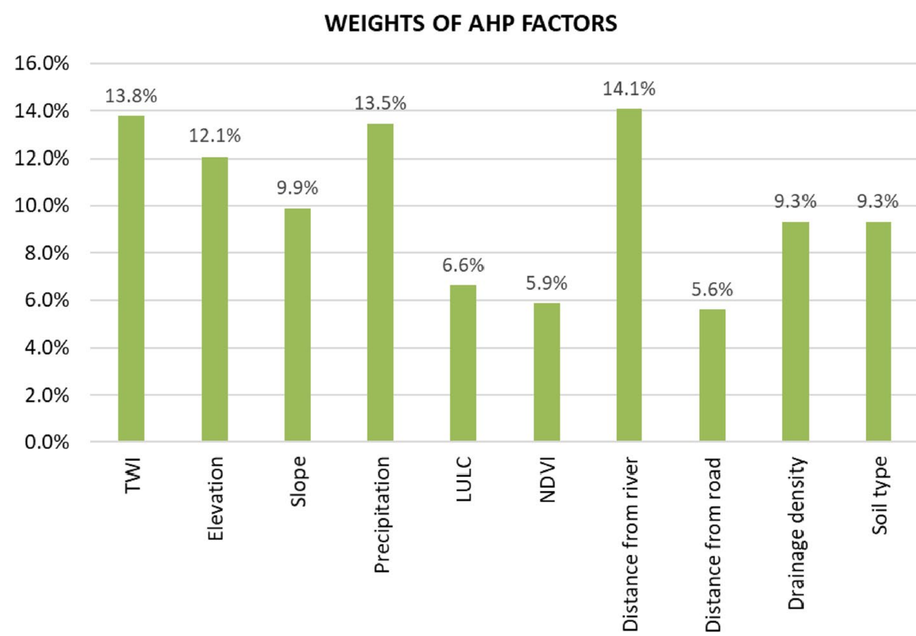


**Fig. 2** Weights of the factors used for the Analytical Hierarchical Process (AHP)

weighted, and combined to create an extensive flood risk map using the AHP. The AHP was used to rank and weight the 10 flood indicators in order to identify areas at risk and determine the degree of flood vulnerability in the Osun River Basin. The relative impact of each pair of flood factors in influencing flood risk is compared. Given its direct influence on the frequency of floods, rainfall data is highly ranked. It was given a high weight because of its substantial impact on flooding, it was combined with additional elements to evaluate total flood susceptibility. TWI was combined with other topographic data to improve the identification of flood-prone areas. It is ranked based on its capacity to identify probable water accumulation zones. Depending on the topographic variability of the area, it is ranked high weight. Since steeper slopes enhance faster runoff, they are given a higher ranking. Given that flooding might be affected by both steep and flat slopes, moderate weight is assigned. It was integrated with TWI and DEM to provide a thorough topographic evaluation. Areas with high drainage densities are given a higher ranking because of their impact on flood dynamics. It was given a moderate weight because good drainage can lessen the effects of flooding. It was combined with river distance and DEM to provide precise mapping of flood danger. The fundamental importance that digital elevation models play in flood simulation accounts for their high ranking. Elevation data influences all other topographic elements, which explains its high weight. It was combined with drainage density and slope to produce a thorough topography profile. The soil's capacity to both absorb and discharge water was used to rate the soil data. Its weight ranged from moderate to high, based on the study area's variety of soil. To evaluate the possibility of surface runoff, the data was combined with information on rainfall and land use. The increased runoff and possible blockages near highways make them higher on the ranking. This flood-causing element has been given a moderate weight, which reflects its indirect influence on flood dynamics. To take human impacts into account, it was paired with LULC and NDVI. Since vegetation can have a considerable impact on soil moisture and surface runoff, but is not the primary cause of flooding, the NDVI is typically given a moderate weight. The direct correlation between distance from rivers and flood risk makes them highly weighted. Given the significant influence that agriculture, urbanization, and natural landscapes have on flood risk, LULC is frequently accorded a high weight. Each factor is compared with every other factors in the matrix created from the pairwise comparison results which is shown in Table 1. The Table shows the percentage of each of the factors and the weights of the factors used for the AHP and Fig. 2 shows the weights of each factor. The weight of each element is determined by calculating the average of each row in the normalized pairwise comparison matrix. The relative significance of each component in the overall assessment of flood risk is reflected in these weights.

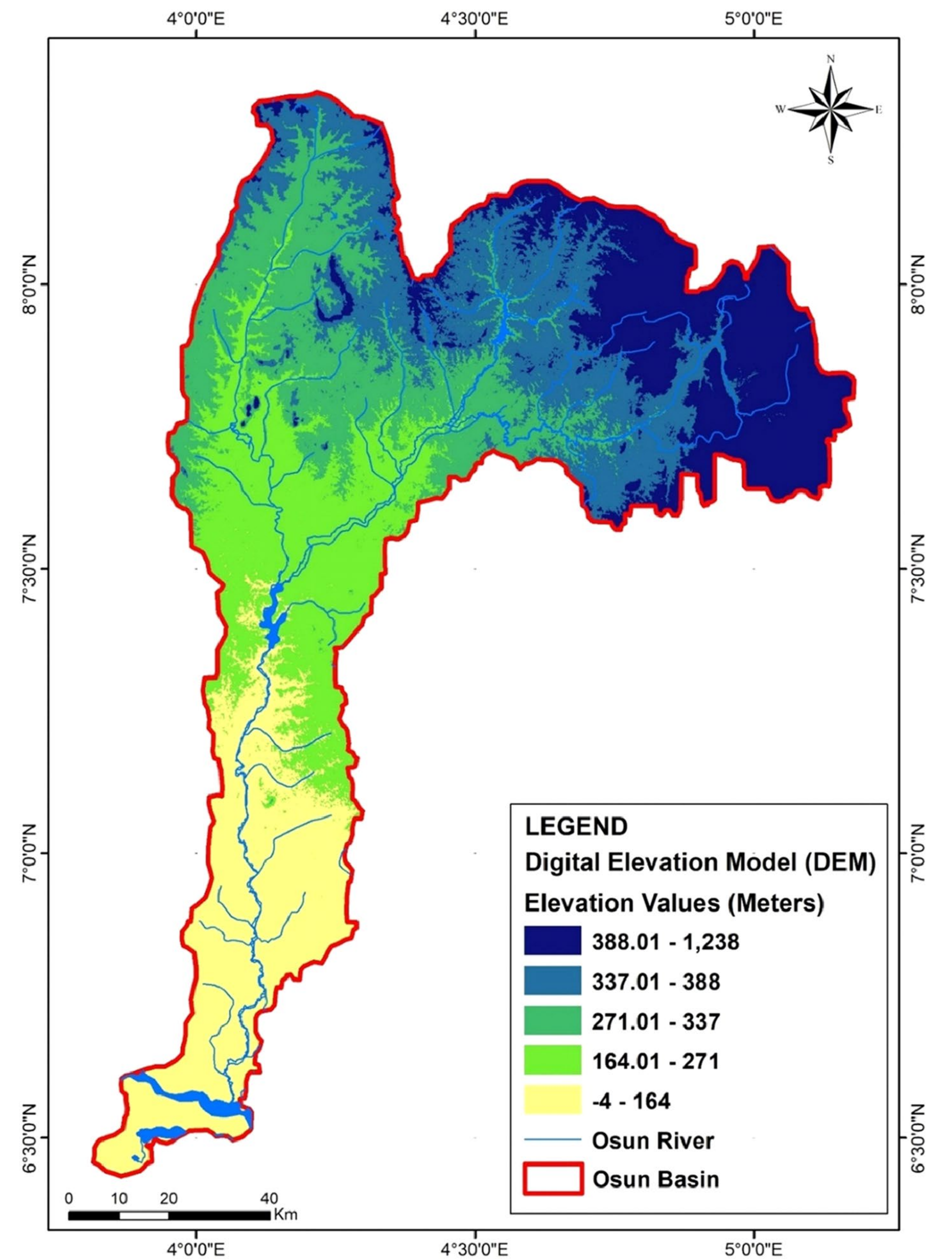


**Fig. 3** Digital elevation model of ORB

## Results and discussion

The conditioning factors are rainfall data, topographic water index (TWI), slope, drainage density, digital elevation model, soil data, distances from roads, normalized difference vegetation index (NDVI), distance from rivers, and land use land cover (LULC) data. There were five categories for flood susceptibility: extremely high, high, moderate, low, and very low.

The result of the elevation values of the basin ranged from 4 m to 1,238 m as shown in Fig. 3. Areas with elevation of 4 m to 200 m are areas with lower elevations which are at greater risk of flooding due to their proximity to bodies of water or their limited ability to drain water, whereas areas with elevation of 600 m to 1,238 m have higher elevations and are less prone to flooding as a result of their increased ability to drain water or their reduced proximity to bodies of water [13]. Areas with elevation ranging from 200 to 600 m have moderate flood susceptibility even though water can still accumulate

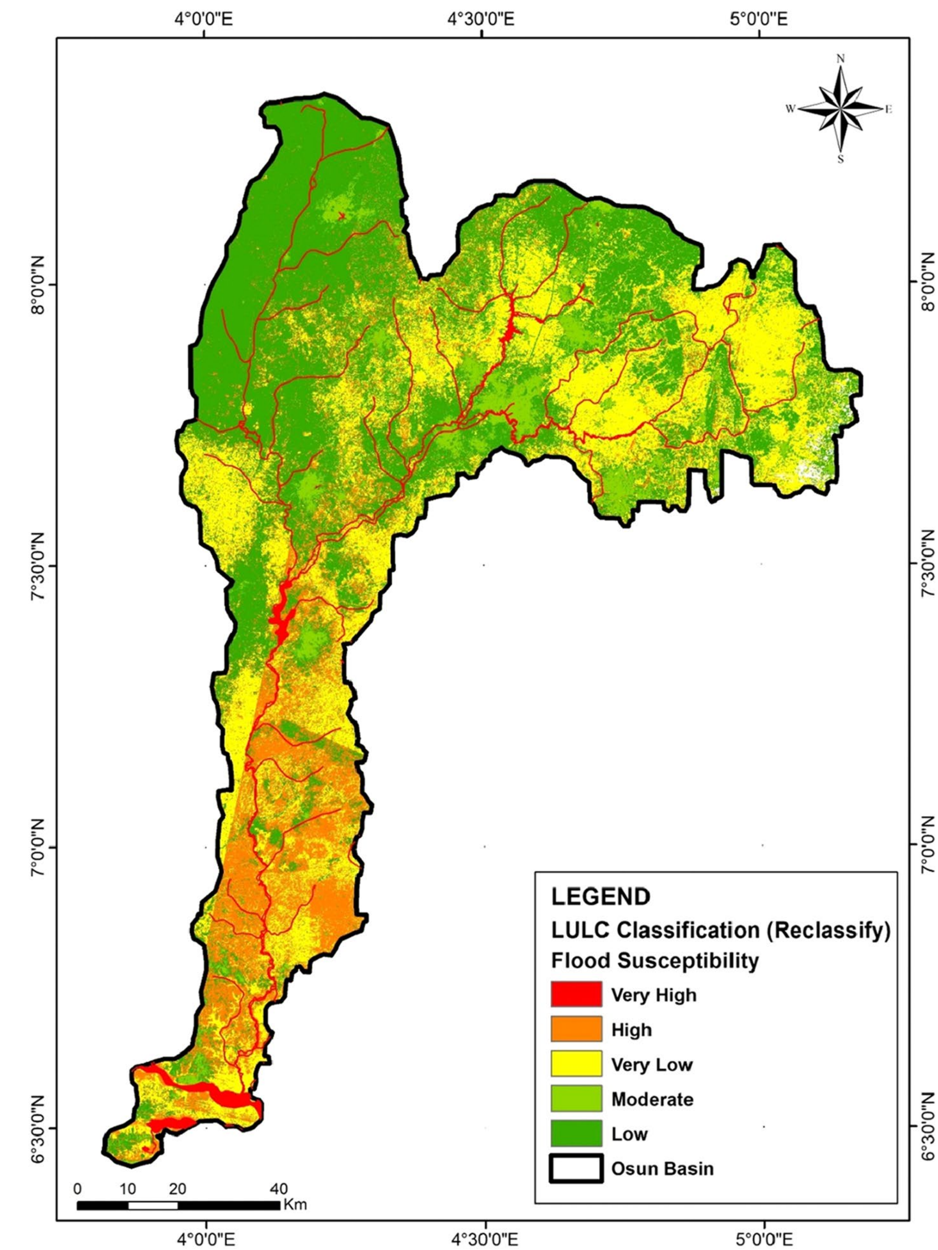


**Fig. 4** Land use land cover classification of ORB

in these areas depending on some other flood causing factors.

The land use land cover was classified into bare surfaces, built-up areas, water bodies, forests and light vegetation. Flooding is very relevant to the classification of LULC. Figure 4 shows the result of the flood susceptibility based on Land use land cover. Table 2 shows the area in kilometre square of the classified items and the percentage of the land cover over the basin. The result shows the total area considered for this study is 10,368.6km$^2$, then the bare surface covers the largest area of the basin which is 4693.1km$^2$. Bare surfaces was 45.3% which comprised areas without vegetation, that is, areas that have no features on them such as rocks, cleared lands and so on. In the basin, bare surfaces make up the majority of the land cover type. These regions usually have little vegetation, which increases surface runoff and raises the danger of flooding because of the poor infiltration capacity. Built-up areas make up 5.7% which are urban areas having buildings and other impervious surfaces. Because of their high runoff and little infiltration, these places are vulnerable to flooding. Forest make up 30.1% which is the dense vegetation cover, this area lowers the danger of flooding by boosting infiltration, decreasing surface runoff, and both. Areas with little vegetation make up the 18.2%. There is an intermediate danger of flooding in these locations due to their moderate runoff and infiltration capacity. Natural water bodies like rivers and lakes are referred to as waterbodies which covers 0.7%. Because these places serve as zones for water storage, they are naturally vulnerable to flooding. Table 3 shows flood susceptibility based on land use land cover classification. The classified area covering 73.2km$^2$ of the basin shows very high susceptibility to flooding which takes 0.7% of the entire basin. 30.1% was the Very Low Susceptibility, which is mainly associated with forested environments. Because forests have a high density of vegetation, they are less susceptible to flooding because of improved water absorption and decreased surface runoff. At 45.3%, the Low Susceptibility falls under the category of bare surfaces. These landscapes are large and may contain regions with modest elevation differences, which reduces flood risk compared to built-up areas, despite the great potential for runoff. 5.7% is the moderate susceptibility, and it is linked to populated places. Although the comparatively smaller area keeps the overall flood sensitivity to a moderate degree, urban infrastructure can make floods worse. There is a correlation between locations with light vegetation and the high Susceptibility of 18.2%. The inadequate absorption and infiltration capabilities of the scant vegetation increases the risk of flooding. The 0.7% very high susceptibility is mostly seen in aquatic bodies. Because these areas naturally gather and store water from rainfall and runoff, they are vulnerable to flooding.

The NDVI ranged from -4 to 0.44 which was categorized into high or low as shown in Fig. 5. The lower the NDVI, the lower the flood susceptibility. The NDVI was calculated from the downloaded Landsat satellite imagery. Flooding and the NDVI have a negative relationship: greater NDVI values suggest a lesser chance of flooding, whereas lower NDVI values imply a higher chance of flooding [47]. The Osun River Basin's NDVI analysis shows a distinct pattern where vegetation density, as indicated by NDVI values, corresponds negatively with the likelihood of flooding. Because of improved water absorption and less runoff, locations with greater NDVI values have lower flood risks, whereas places with lower NDVI values have higher flood risks.

**Table 2** Land use land cover classification of ORB

| S/N | Class name | Area (Km$^2$) | Per cent |
|---|---|---|---|
| **1** | Bare Surfaces | 4693.1 | 45.3 |
| **2** | Built-up Area | 588.1 | 5.7 |
| **3** | Forest | 3123.3 | 30.1 |
| **4** | Light Vegetation | 1890.9 | 18.2 |
| **5** | Waterbody | 73.2 | 0.7 |
| | Total | 10368.6 | 100.0 |

The rainfall around the basin ranged from 3.7 mm to 4.9 mm as shown in Fig. 6, rainfall is a major factor that causes flooding. Therefore, the more precipitation the greater the rainfall around the basin ranging from 3.7 mm to 4.9 mm as shown in Fig. 6, rainfall is a major factor that causes flooding. Therefore, the more precipitation the greater the vulnerability to flooding [25]. The amount of rainfall has a significant impact on flood susceptibility. According to the rainfall data gathered, the Osun River Basin saw rainfall ranging from 3.7 mm to 4.9 mm, as seen in Fig. 6. The amount of rainfall varies significantly throughout the basin, which has a substantial impact on the flood danger in various locations especially at the lower part of the basin.

The distance to the river was measured in meters ranging from o meters to 20,000 m. Certainly, the shorter the distance to the river, the higher the flood susceptibility. Figure 7 shows the classification based on the distance to the Osun River. In the same way, the distance of the river to the road was also measured in meters ranging from 0 m to 6,800 m. The distance was classified from very low to very high as shown in Fig. 8.

The result of the slope ranged from less than zero to 1,197.59 per cent rise. Figure 9 shows the classification of the slope in the river basin from very low to very high. Steep slopes produce higher speeds for water to flow than flatter or gentler slopes, therefore, runoff may be disposed of more quickly [25]. The Osun River Basin has a slope that varies from less than zero, which denotes a little fall or flat sections, to 1,197.59 per cent, which is a strong increase. Water flows more quickly down steep

**Table 3** Flood susceptibility based on land use land cover classification of ORB

| S/N | LULC | Area (Km$^2$) | Per cent |
|---|---|---|---|
| **1** | Very Low | 3123.3 | 30.1 |
| **2** | Low | 4693.1 | 45.3 |
| **3** | Moderate | 588.1 | 5.7 |
| **4** | High | 1890.9 | 18.2 |
| **5** | Very High | 73.2 | 0.7 |
| | Total | 10368.6 | 100.0 |

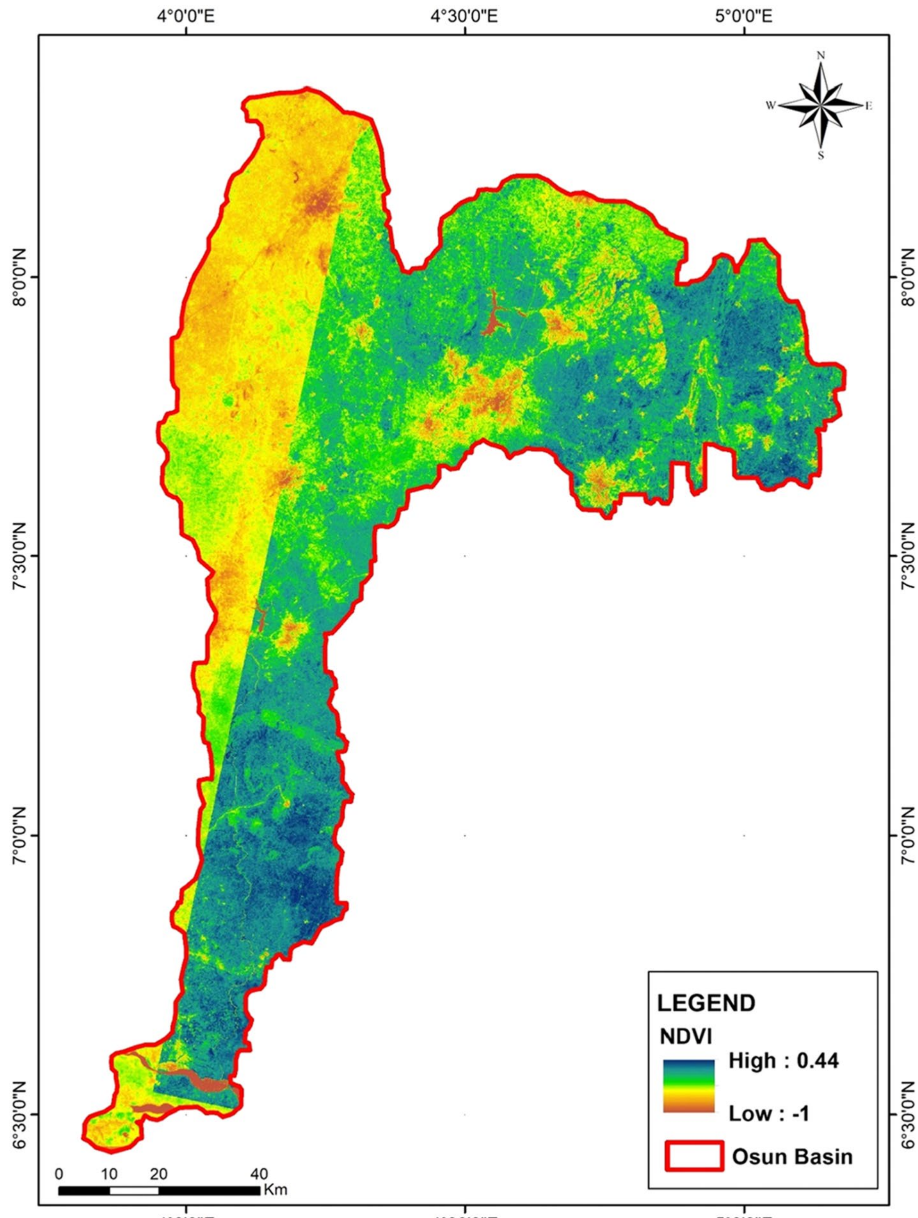


**Fig. 5** Normalized Difference Vegetation Index (NDVI) of ORB

slopes. Water doesn't stay on the surface for very long because it goes off rapidly. It is less likely for the swiftly flowing water to build up and result in flooding. However, under other circumstances, the quick runoff may cause flash floods down the hill when the slope lessens. The Osun River Basin's slope analysis demonstrates how greatly topographic diversity affects flood susceptibility. While gentle slopes and flat areas are more vulnerable to floods because of slower water movement and increased accumulation potential, steep slopes tend to lessen the risk of flooding in their immediate vicinity by facilitating quick water runoff.

The soil type was classified into five which are; clay, clay loam, silt loam, loam and loamy sand. Soil characteristics play a crucial role in flood susceptibility, and the composition of soil in terms of clay, silt, and sand particles is particularly significant [15]. The classification of the soil type in ORB is shown in Fig. 10.

The topographic wetness index (TWI) is based on the knowledge of how much water is distributed throughout a river basin. Higher TWI classes indicate increased

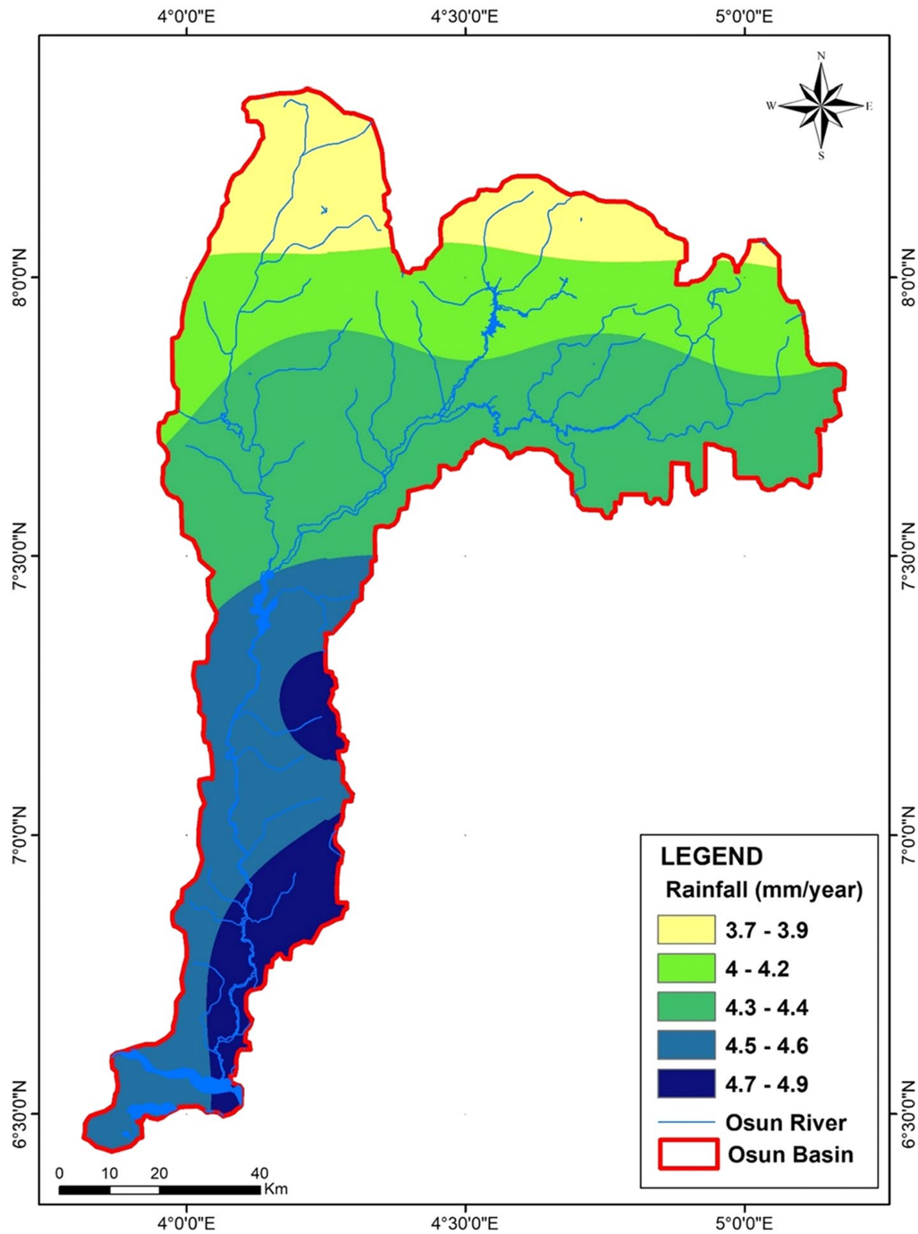


**Fig. 6** Rainfall of ORB

likelihood of floods in the river basin [46]. TWI measures the geographical distribution of soil moisture, which is directly associated with the danger of flooding and surface runoff. The map of flood susceptibility shown in Fig. 11 was created by classifying the TWI values, and this map aids in understanding the spatial distribution of flood risk throughout the Osun River Basin. There are several classifications within the TWI value range (1.7 to 26) that correspond to different levels of flood susceptibility. Based on the TWI values, this classification helps in identifying the places with high, moderate, and low flood hazards. Based on the potential for water buildup, the TWI study of the Osun River Basin shows the area's variability in flood risk.

The drainage density was measured in meters and it ranged from 0.032 to 0.98 for the ORB. It was further classified based on flood susceptibility as shown in Fig. 12. The larger drainage density, causes the water discharge to rise [39]. Some part of the area has a low density of drainage channels, which means there are fewer or longer distances between channels. The low drainage density in the area is 0.032. A high density of drainage

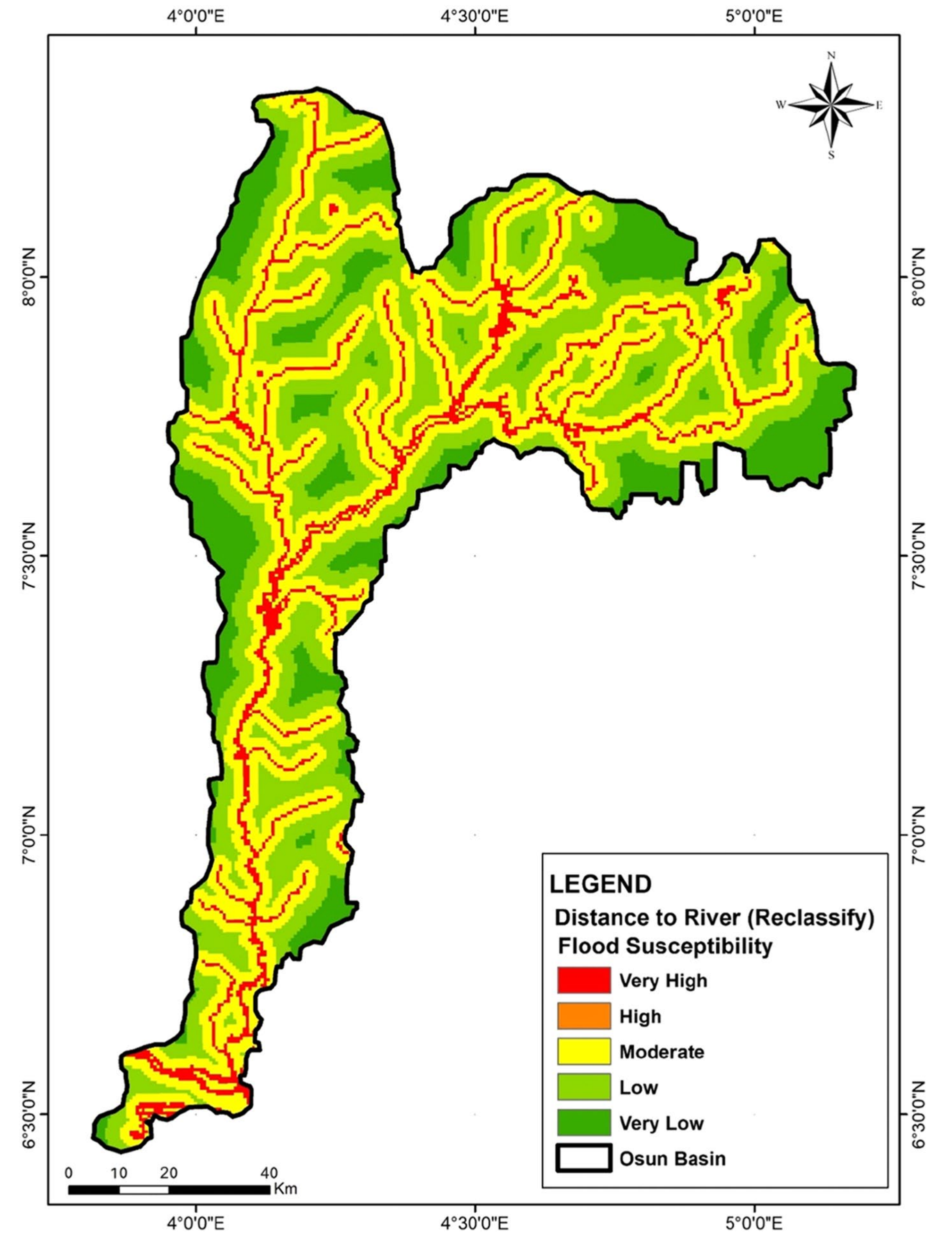


**Fig. 7** Distance to the ORB

channels with more frequent and shorter channel spacing was represented by a high drainage density of 0.98.

The created maps were extracted at every 100-m interval. The 10 conditioning flood factors were weighed based on their importance using the Analytic Hierarchy Process (AHP). Figure 13 shows the result of the combination of the 10 components in the flood vulnerability maps of the ORB. The flood susceptibility was characterized as high, moderate, low and very low. Flood risk is divided into five categories on the map according to risk assessment: Very Low (green), Low (yellow), Moderate (blue), High (orange), and Very High (red). The regions most at risk are shown in red, denoting those that are most vulnerable to flooding. Meanwhile, the water bodies are probably going to affect the flood danger in nearby places based on Geographical Features. The concentration of the high-risk zones (orange and red) around riverbanks and low-lying areas suggests that these places are more vulnerable to flooding because of their close proximity to water sources. This map can be utilized for infrastructure development to reduce flood hazards, disaster management, and urban planning. Flood protection and

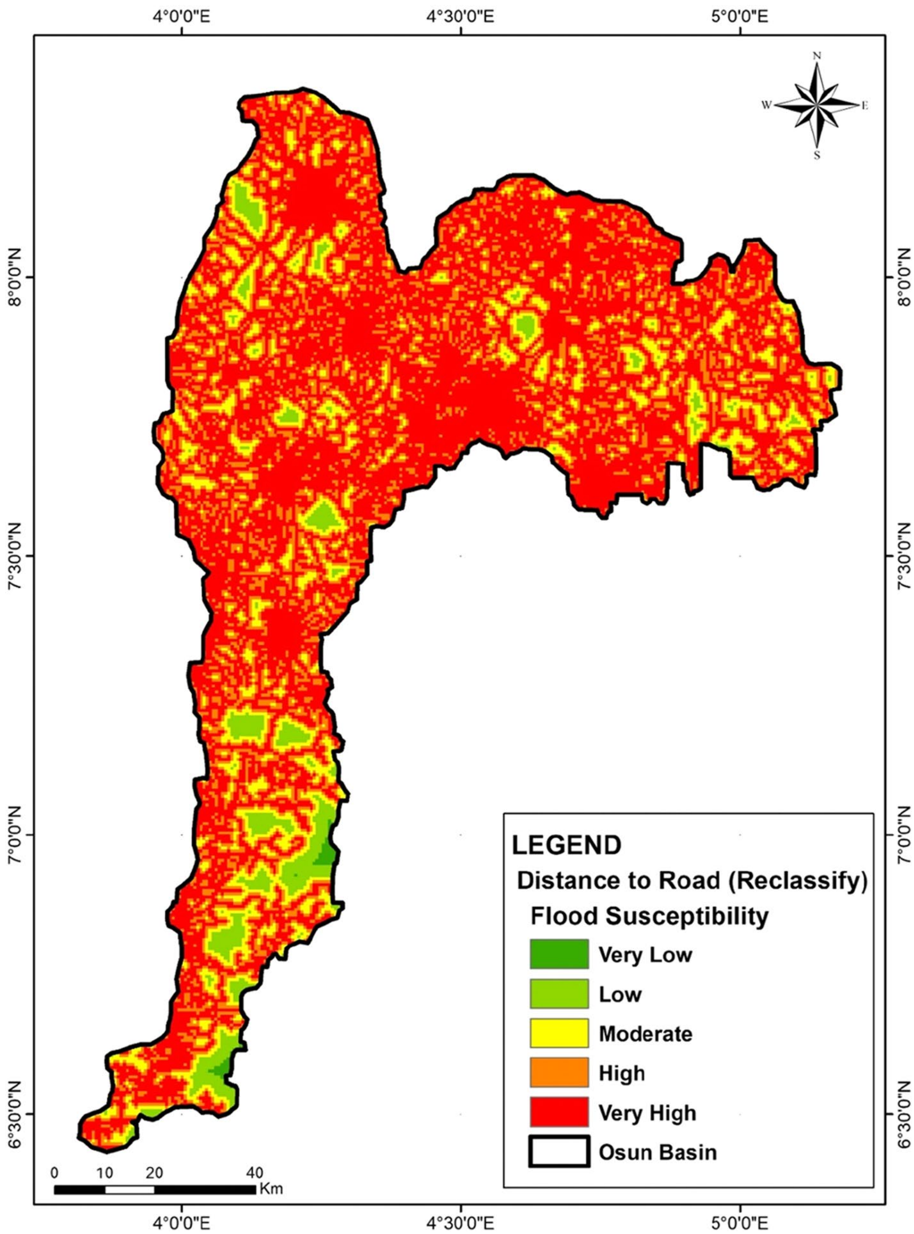


**Fig. 8** Distance of road to the ORB

disaster preparedness measures should be emphasized in areas with high and extremely high risk.

The topographic wetness index (TWI) is based on the knowledge of how much water is distributed throughout a river basin. Higher TWI classes indicated an increased likelihood of floods in the river basin [46]. The results ranged from 1.7 to 26 and the range based on the classification for flood susceptibility to produce the map and the classification is shown in Fig. 11. TWI is a measure of how wet the area is and is used to identify possible floodplains in river basins. It was derived from information produced from DEM utilizing slope and flow accumulation functions. The drainage density was measured in meters and it ranged from 0.032 to 0.98 for the ORB. It was further classified based on flood susceptibility as shown in Fig. 12. The larger drainage density, causes the water discharge to rise [39].

The elevation of the Osun River Basin varied from 4 to 1,238 m. Because of their proximity to the river and inadequate drainage, lower elevations (4–200 m) are more likely to flood, whereas higher elevations (600–1,238 m) are less likely to flood because of improved drainage.

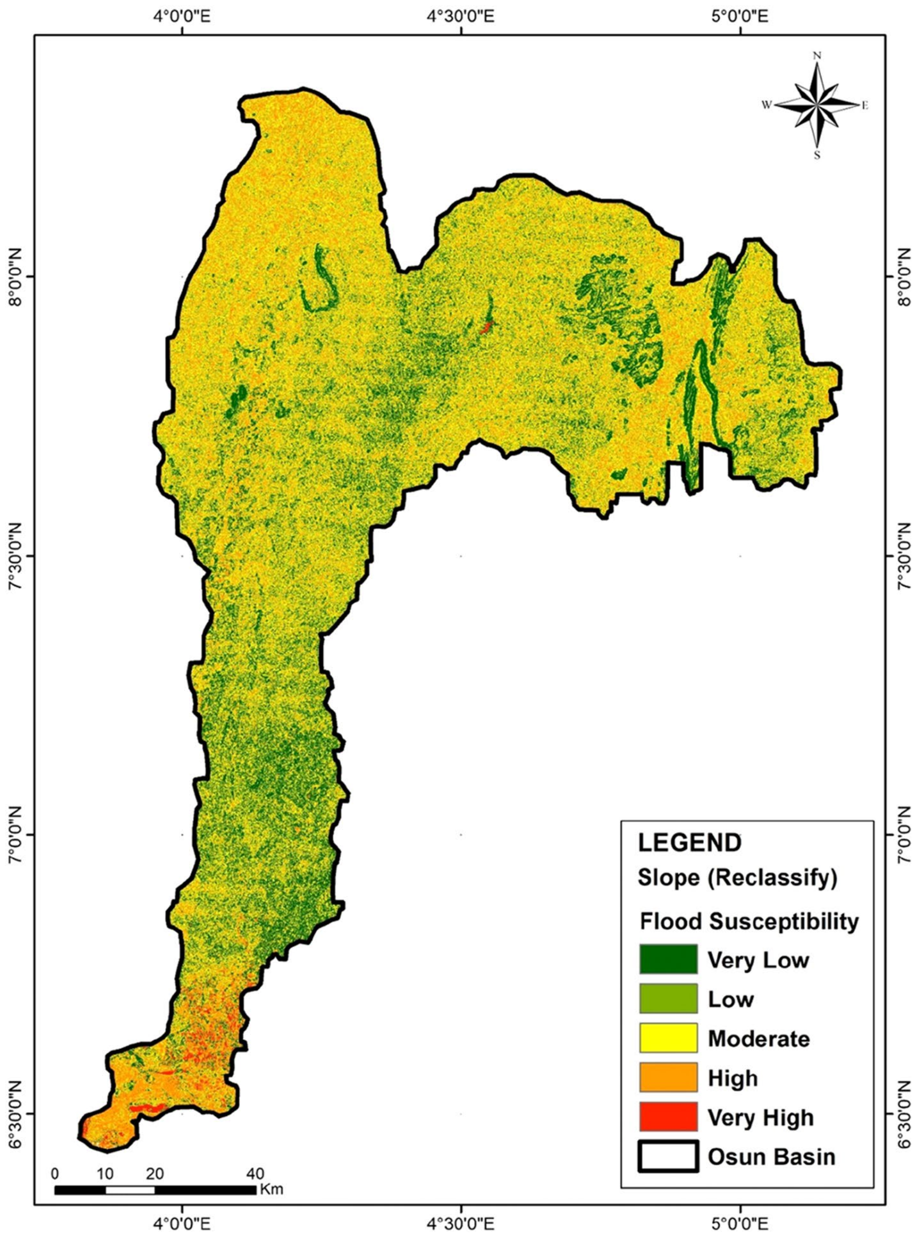


**Fig. 9** Slope in the ORB

Danu [12] similarly effectively ranked elevation in Dammam, Saudi Arabia for flash floods. In conclusion, this study used maps created by Geographic Information Systems (GIS)-based spatial analysis, such as APH, to identify the spatial patterns of vulnerability of flooding of the Osun River basin. Danu [12] similarly carried out an Analytic Hierarchy Process (AHP) evaluation of flood-prone areas to improve flood resilience in Dammam, Saudi Arabia. Danu [12] evaluated five flood-causing factors, with a priority weight of 32%, the results show that rainfall has the largest chance of causing flash floods, followed by land use (19%) and slope (18%). The least significant contributing characteristics were determined to be soil type and elevation, with priority weights of 15% and 16%, respectively. According to the LULC ranking and weight, built-up areas (5.7%) and bare surfaces (45.3%) are the most vulnerable to flooding because of impermeable surfaces and high runoff. Forests (30.1%) and light vegetation (18.2%) reduce the risk of flooding by improving infiltration and reducing runoff, while water bodies (0.7%) are naturally prone to flooding because of water accumulation. The basin has 3.7 to 4.9 mm of rainy seasons. The

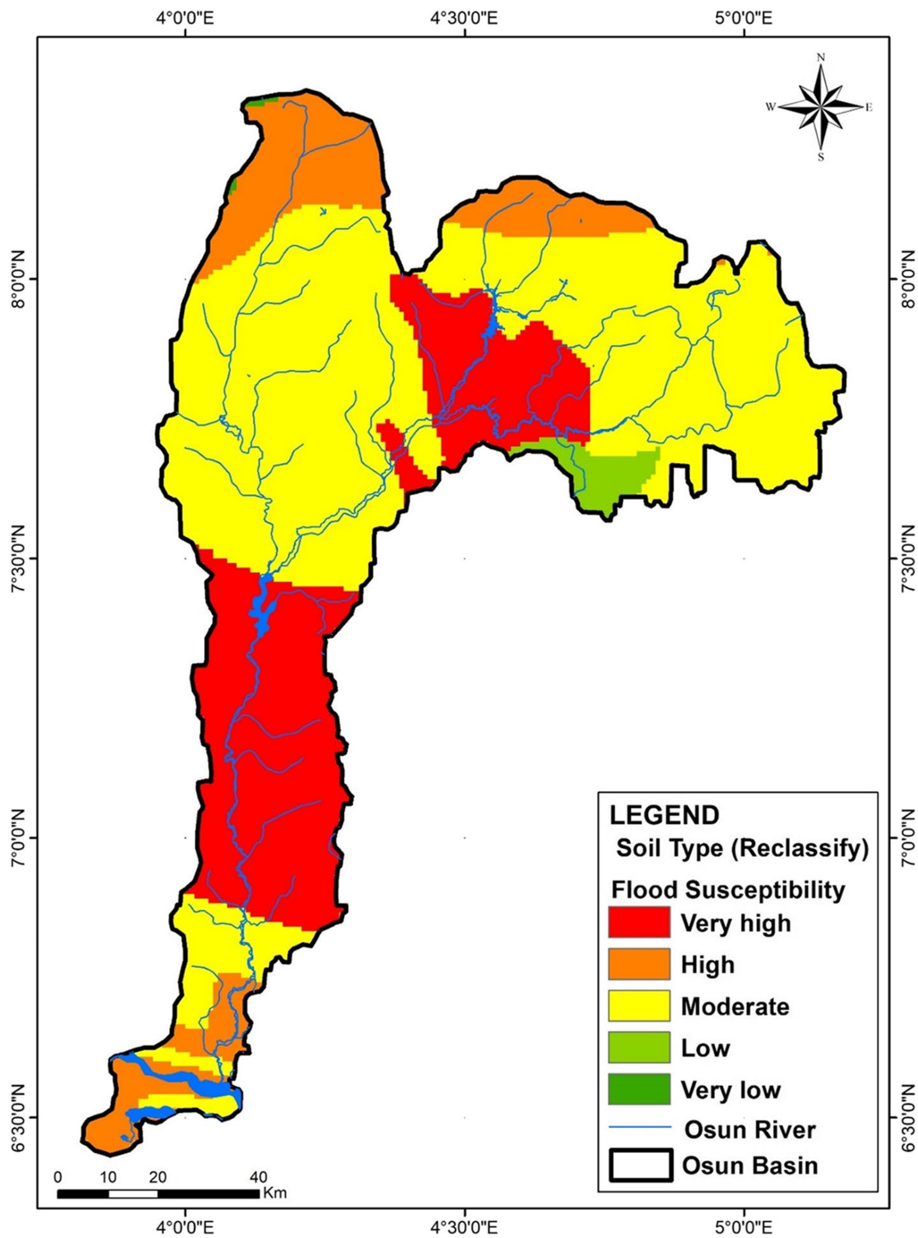


**Fig. 10** Soil type and flood susceptibility in the ORB

fluctuation in rainfall throughout the basin has a substantial impact on flood vulnerability. Higher precipitation is strongly correlated with increased flood risk, especially in lower elevation and flat places where water accumulation is more likely. Lower NDVI values suggest greater flood susceptibility due to reduced vegetation cover, leading to increased runoff. Conversely, higher NDVI values indicate better vegetation cover, enhancing water absorption and reducing flood risk. The slope values were found to range from less than zero to 1,197.59 per cent growth. Faster water runoff is made possible by steep slopes, which lessens the chance of flooding. However, places that are level or have a gentle slope collect more water, which makes flooding more likely. The variance in slope emphasized how crucial it is to take topographic variables into account when evaluating flooding. Similarly to this study, Hasanuzzaman et al. [18] assessed flood Vulnerability Torsa- Raidak River basin using AHP. Rainfall, LULC and distance from the river contributed the most to causing flood in the Torsa- Raidak River basin as the main causative factors. TWI levels in this study indicated possible water accumulation and ranged from 1.7 to 26.

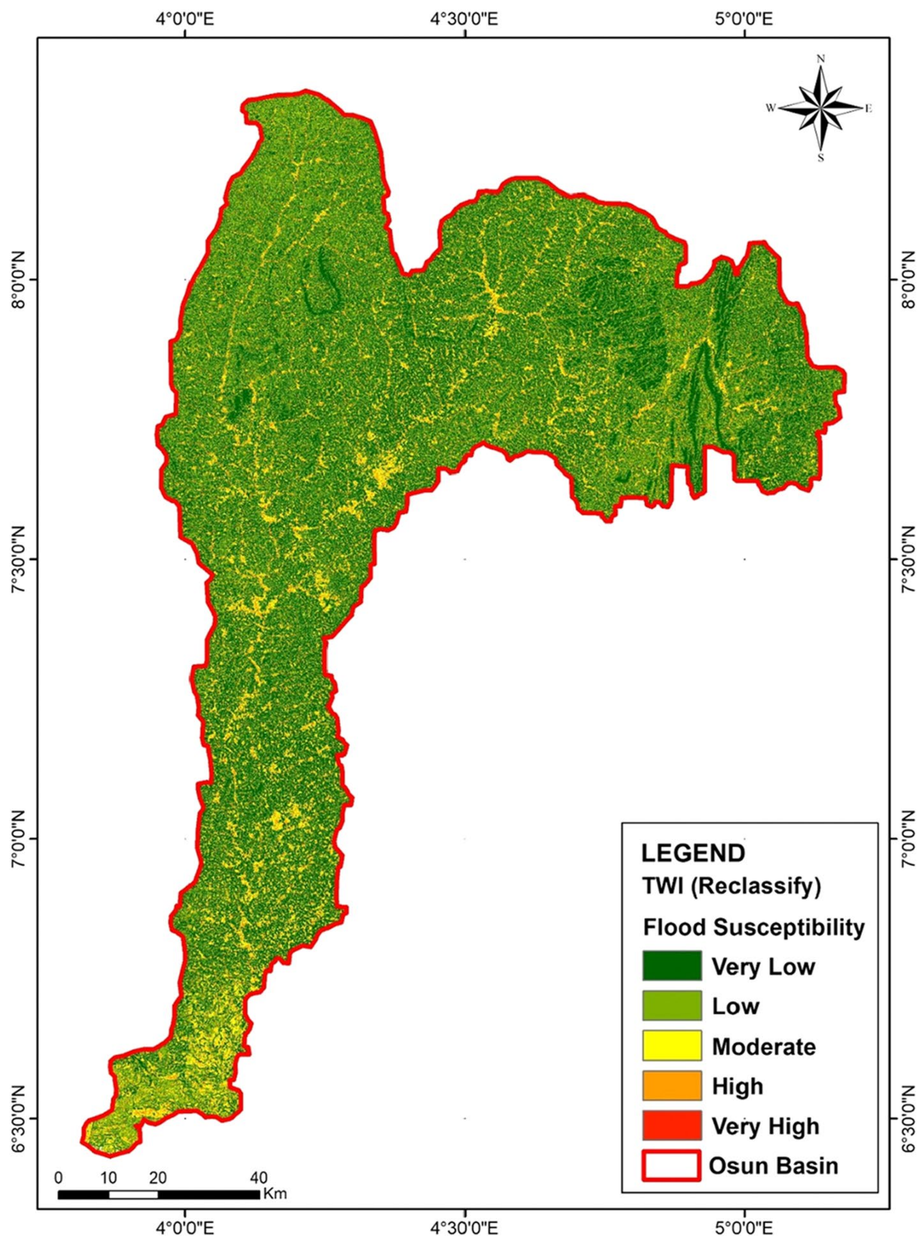


**Fig. 11** Topographic water index in the ORB

Given their greater water retention, higher TWI values signify a higher risk of flooding. The TWI analysis used patterns of water distribution to identify areas that are differentially vulnerable to flooding. Lappas and Kallioras [24] assessed flood Susceptibility in a Central Greek River Basin using the Analytical Hierarchy Process (AHP). It was also observed that TWI had the most influence (weight) on the assessment of floods caused by both natural and man-made factors. The range of drainage density is 0.98 m to 0.032 m. Areas with higher drainage densities are less susceptible to flooding because they can manage runoff better. Because of ineffective water transportation, areas with lower drainage densities are particularly susceptible. Burayu et al. [11] used the combination of GIS, remote sensing, and the analytical hierarchy process (AHP) to identify flood-prone and risk areas in the Oromia region, Ethiopia. Eight factors were evaluated including the drainage density which ranged moderately as a flood-causing factor in the case study.

The created maps were extracted at every 100-m interval. The data was classified based on flood

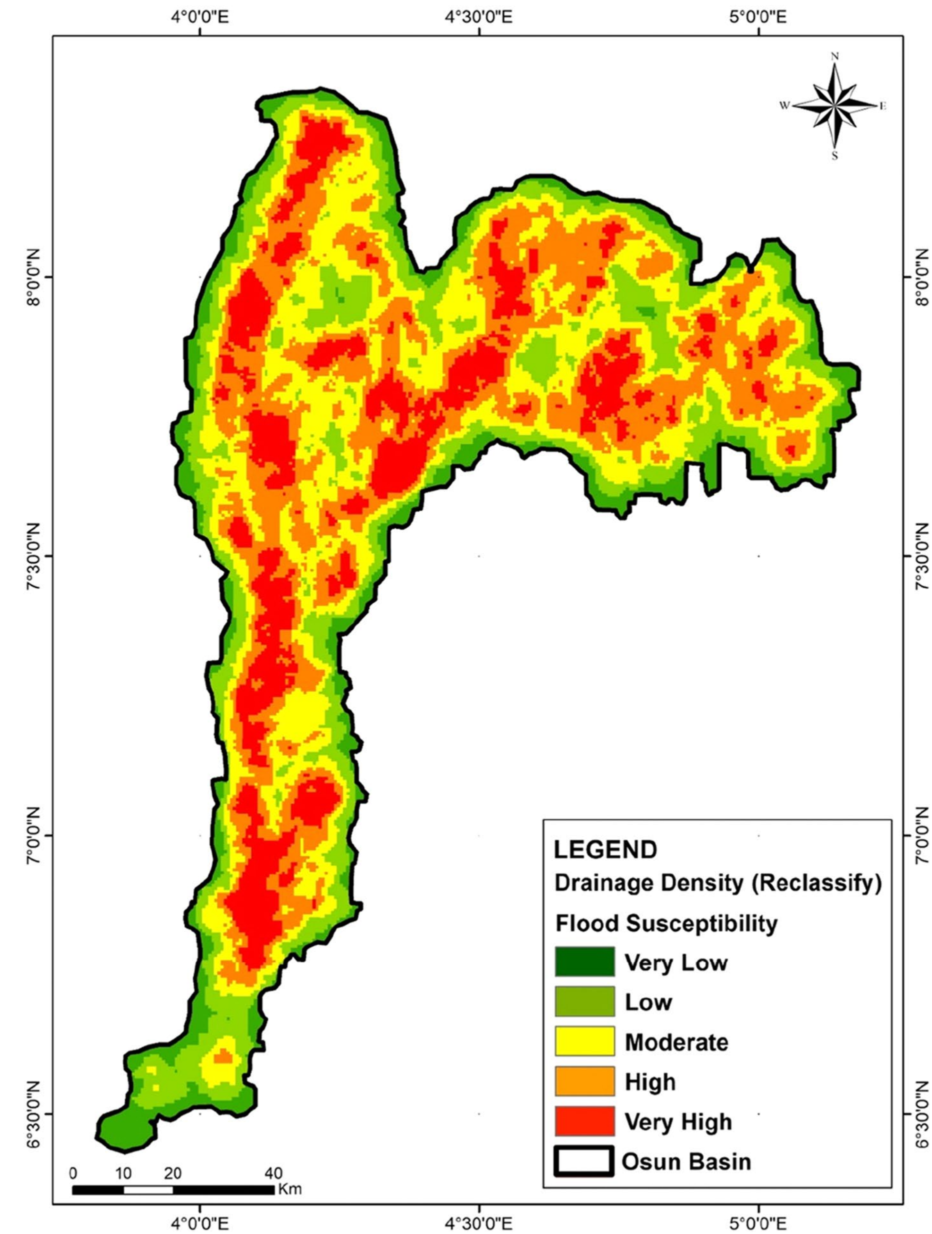


**Fig. 12** Drainage density of ORB

susceptibility as; Very low, Low, Moderate, High and Very High. The 10 conditioning flood factors were weighed based on their importance using the Analytic Hierarchy Process (AHP). Figure 13 shows the result of the combination of the 10 components in the flood vulnerability maps of the ORB. The flood susceptibility was characterized as high, moderate, low and very low. From the map, it was identified that over 200 locations are highly susceptible to flooding. This calls for action by stakeholders and policymakers to avoid tragedies that come with flooding.

## Conclusion

Using a variety of conditioning factors, this study provided the assessment of flood susceptibility in the Osun River Basin with a detailed understanding of the flood risks throughout the basin. Five classes of flood sensitivity were identified based on the ten flood-causing factors: very low, low, moderate, high, and extremely high. Flood-prone zones in the Osun River basin were identified using

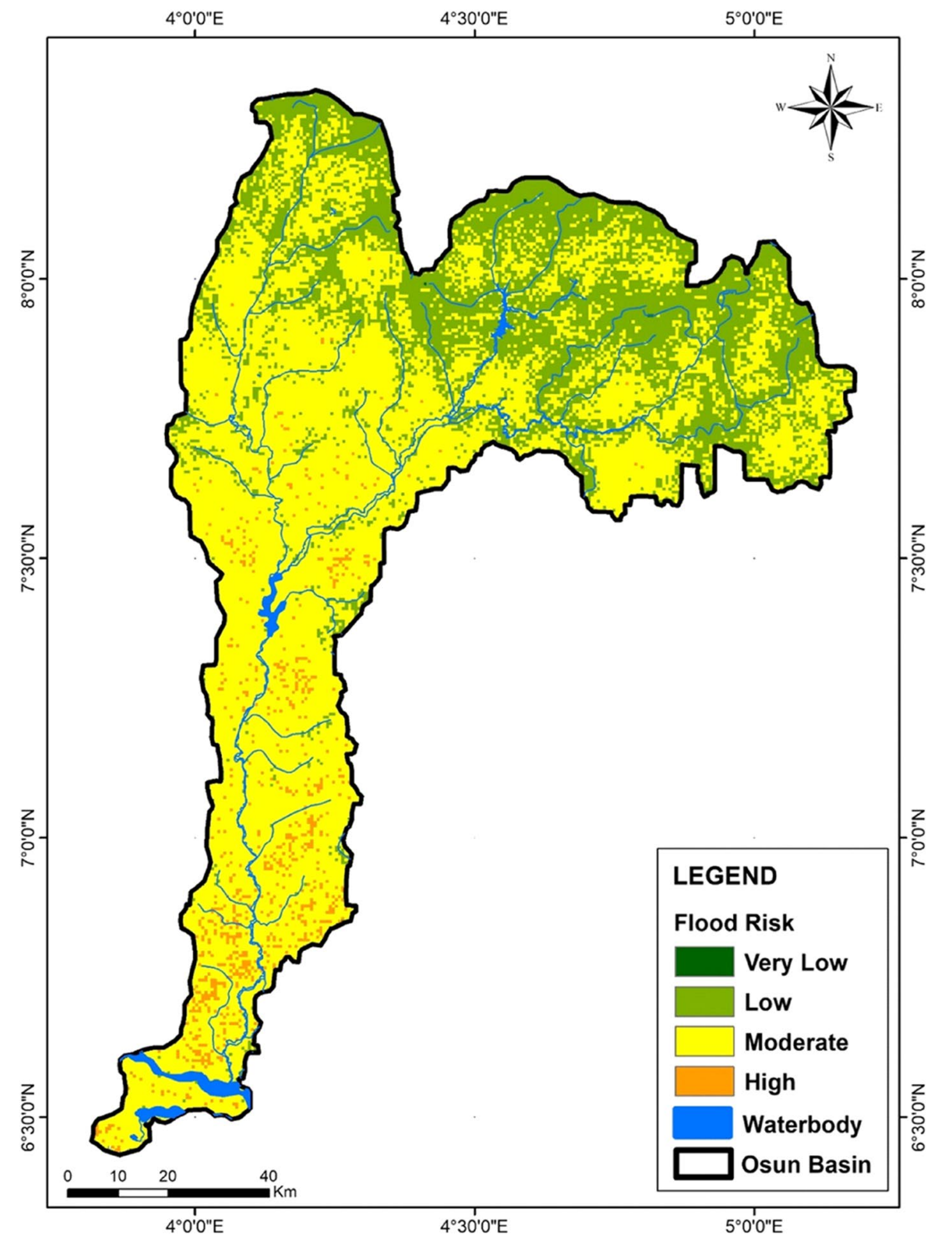


**Fig. 13** Flood susceptibility of the ORB

the Analytic Hierarchy Process (AHP) and Geographic Information Systems (GIS)-based spatial analysis. The results showed that Ekiti State has the lowest flood susceptibility which can be caused by the Osun River flooding. Oyo state is susceptible to moderate floods from the river flooding. Osun State and Lagos State have some locations that are very susceptible to flooding from the tributaries of the river. Ogun state is the most affected, most places that are very highly susceptible to flooding from the tributaries are found in areas such as Ijebu North, Ijebu East Ijebu, North East and Ijebu Ode. Future research should focus on integrated strategies that consider the interplay between the physical, social, and policy components, creating opportunities for effective interventions to increase flood resilience and decrease the effects of floods on the environment and people living along the tributaries of Osun River. As a result, this study gives legislators, urban planners, and local stakeholders an excellent framework to help them make decisions about how to reduce flooding in other locations with the same degree of unpredictability. Future work to be done is carrying out another set of weight on the result in each of the states found in the river basin, this will aid identification of the most significant flood-causing factors in each state.

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**Authors' contributions**
Ogundolie Oluwatosin Iyanu: Conceptualization, methodology, Funding acquisition, Formal analysis and investigation and Writing—original draft preparation, review and editing: Olabiyisi, Stephen Olatunde: Supervision, Conceptualization; Analysis; Writing—original draft preparation, review and editing: Rafiu Adesina Ganiyu: Supervision; Methodology; Formal analysis, Writing—review and editing Jeremiah Yetomiwa. Sinat: Writing—review and editing, analysis. Ogundolie Frank Abimbola: Conceptualization, Resources and Writing—review and editing.

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**Availability of data and materials**
The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Competing interests**
The authors declare no competing interests.

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