# Flood hazards characterization using multi-criteria decision and flood frequency analysis in Osun River Basin, Nigeria

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# Abstract

Flooding is regarded as one of the world's most dangerous natural disasters with great highly devastating social, economic and environmental impacts. This study employs the use of a GIS-based multi-criteria decision approach (MCDA) and flood frequency analysis to assess the flood potential zones and magnitudes in the Osun River basin. Six flood causative factors (soil type, elevation, slope, drainage density, distance from the river, land use land cover) were considered and integrated into the Geographical Information System using analytical hierarchy process (AHP) and weighted overlay with a consistency ratio of 0.04. The output was classified as having a flood potential ranging from very low to very high. HEC-HMS hydrological model was used to simulate previous potential flood discharges from 1981 to 2020 within the river basin. A basic descriptive analysis was performed to understand the hydrological characteristics of the basin from the previous records. We analysed the flood frequency from the simulated stream peak flow using the Gumbel frequency distribution method. The results from the analysis showed that 11% of the study area is highly prone to flooding. The moderately prone zones cover more area (82%) and 7% of the area is not prone to flooding. The peak discharge for the simulation period ranged from 531.5 to 1846.8 $m^3$/s. The peak discharge (1846.8 $m^3$/s) at the basin has a 41-year recurrence interval. Using the Gumbel's extreme value distribution method, the calculated discharge flood lies within 1117.43 $m^3$/sec to 1858.51 $m^3$/sec for 5 years to 150 years' return period for the Osun River basin

# 1. Introduction

Globally, flood hazard is one of the most frequently occurring natural hazards with extreme impacts on lives and properties (Doocy et al., 2013; Freire et al., 2016; Komolafe et al., 2018). It is estimated that approximately 2.2 billion people (about 29% of the population of the world), lives in places that will experience at least 1 in 100-year flood events (Rentschler and Salhab, 2020, WRI, 2020; UNISDR, 2017). These enormous exposures are probably at risk of severe flooding in the future whenever extreme events occur. In Nigeria, recent flood events had caused lots of damage to the economy and the environment (Bariweni et al., 2012; Etuonovbe, 2011). In 2012 for instance, devastating flood events had killed 363 people and displaced over 2.1 million people (Social Action, 2012). The floods affected 30 of Nigeria's 36 states, according to the National Emergency Management Agency (NEMA). The floods were characterized as one of the worst in 40 years, and an estimated seven million people were affected (Komolafe et al., 2015; UNCHA, 2012). The floods were predicted to have caused N2.6 trillion in damages and losses. In some parts of Oshogbo, Ogun State and along the Osun River basin, flooding has been a recurring problem, which has caused various degrees of damage and destruction to lives and properties (Otomofa et al., 2015).

The increasing trends in the frequency of flooding globally had created serious concern for effective mitigation and adaptation measures to stem the potential future disasters (IPCC, 2007; Pankaj and Kumar, 2009). Since it's practically impossible to completely guide against floods, various measures are necessary to reduce its potential effects on mankind (Mahfuzur et al., 2021; Olorunfemi et al., 2020). This would require the integration of methods for accurate prediction and delineation of possible risk zones that can provide information for policy and disaster risk reduction plans. The assessment of vulnerability, risk, and disaster management would require a large amount of multi-temporal geospatial and multi-date hydrological data that can be analysed using geographic information system (GIS) and hydrological model, respectively (Chopra et al., 2005; Dutta et al., 2009; Hajam et al., 2013; Ibitoye et al., 2020; Pankaj and Kumar, 2009 ). Most studies apply these methods in flood evaluation separately; however, integrating the two approaches is expected to provide accurate estimation and prediction of potential flood hazard zones and risk for mitigation and adaptation measures.

A flood hazard zonation map shows the spatial extent of potential flooding areas; this can be presented quantitively and qualitatively. The simplified classification of flood hazards into classes of varying degrees of risk (very high, medium, low, or very low hazard) provides information for the - decision-makers on how to prioritise zones for risk management, evacuation, mitigation and adaptation measures (Getahun and Gebre, 2015). Apart from the qualitative zoning of flood hazard extents, there is a need to quantify the expected volume of water in the river for the comprehensive development of water management policy and risk reduction. Estimation of the potential discharges or river flows at different future occurrences, provides information on whether there will be flooding or a shortage of water.

Multi-criteria decision analysis (MCDA) is known to be an indispensable tool for evaluating intricate decision problems that involve multiple data and criteria (Hwang and Yoon 1981; Malczewski, 2006). The GIS-based multi-criteria analysis incorporates various factors responsible for flooding based on their influence (Boroushaki and Malczewski 2010). It is a set of methods employed to organize and estimate different opinions based on many conditions and objectives (Voogd, 1983). Among many methods of MCDA, AHP has proven to be very effective and popular in flood risk mapping and assessment (Saaty, 1990). According to Fernandez and Lutz (2010), the AHP method applied in a GIS environment possesses a powerful approach to developing natural hazards zonation map with a certain degree of accuracy. It is perhaps the most understandable, - cost-effective and easy method of MCDA for flood hazards and risk analysis (Elsheikh et al., 2015; Komolafe et al., 2020).

In an ungauged and data-scarce, river basins such as the study area, estimation of river discharges using hydrological models and the determination of flood frequency are very important. Accurate estimation of potential flood events, their intensities and return periods are necessary steps in preventing the overwhelming negative effects of floods in most river basins (Mishra and Herath, 2012). Constant and accurate river discharge prediction and forecast are required for water resource planning, water management, disaster planning and mitigation and cost-benefit analysis (Sandeep and Abinash, 2020). Flood-frequency analysis is very useful in the predictions of future flood magnitudes and potential risks. Generally, the frequency of flood occurrences is determined from past rainfall and river discharge data using either empirical or theoretical probability statistical approaches. It deals with the analysis of the observed peak discharges to evaluate future probabilities of exceedance (Archer, 1998). This study embraces the use of integrated hydrological modelling and AHP approaches to identify the intensity and frequency of potential extreme events in the study area and also delineate the potential hazard zones, for mitigation, adaption and flood risk reduction plans.

# 1.1 Study Area

Osun drainage basin is located within latitudes 7$^{o}$35' and 8$^{o}$00' north and longitude 4$^{o}$30' and 5$^{o}$10' east of southwestern Nigeria (Fig. 1). Osun river basin is part of the upland area that extended from Ekiti state to the lowland area of Osun state (Akinwumiju, 2015). It is characterised by a long rainy season that occurs between March and November yearly with the maximal rainfall of 1,500–1,700mm per annum. The rainy season in the basin is normally characterized by two maxima rainfall with peaks in July and September/ October (Adediji & Ajibade, 2008). Relative Humidity rarely dips below 60% and fluctuates between 75% and 90% for most of the year (Akinwumiju, 2015).

## 2. Methodology

The study made use of multi-criteria analysis -AHP and the analysis of flood frequency from the output of HEC-HMS hydrological model to predict the potential flood zones and frequency in the Osun-River basin. Firstly, various flood causative factors were generated from remotely sensed data and integrated to MCA using the AHP technique. Hydrological modelling was carried out using HEC-HMS to estimate the potential discharges for the past 40 years. Subsequently, the peak discharges were analysed to derive the flood frequency using the Gumbel distribution.

# 2.1 Data and Data Source

Both primary and ancillary data were utilized for the analysis in the study. Soil data was derived from the FAO Harmonized world soil database (HWSD), available on FAO's website (Table 1). Elevation data made use of The Shuttle Radar Topographic Mission (SRTM), a joint effort of the National Geospatial-Intelligence Agency (NGA) and the National Aeronautics and Space Administration (NASA), launched on February 11, 2000 (USGS, 2008). The land use land cover data was derived from Landsat 8-OLI with 30-meter spatial resolution from the United States geological survey (USGS)'s website. The lithology of the study area was extracted from the global geological data from, USGS. Rainfall data were downloaded from the TRMM's website as shown in Table 1.

Table 1
Data sources

| S/N | DATA | SOURCE | PURPOSE |
|---|---|---|---|
| 1. | SOIL | FAO Digital Soil Map of the World (HWSD). | MCDA and hydrological modeling |
| 2. | Landsat – 8 OLI | USGS | For land use land cover analysis. |
| 3. | SRTM DEM | USGS | To get the elevation, slope, and some other hydrological parameters such as flow direction, stream order, and drainage density. Hydrological modelling |
| 4. | Geology | USGS | The lithology of the study area |
| 5. | Rainfall | TRMM | Hydrological modelling |
| 6. | River discharges | Ogun-Oshun River basin Authority | Validation of the simulated discharges |

## 2.2 Multi-criteria Data Analysis (MCDA)

## 2.2.1 Derivation of flood Causative factors

Six thematic flood causative factor layers namely; elevation, slope, Euclidean distance to river, land use/land cover, soil and drainage density were subjected to multicriteria analysis in GIS to derive possible zones for flood hazards. Each of these factors was derived from both remotely sensed and ancillary data, and was generated as raster, reclassified and hierarchical based on their effect on floods. All layers were georeferenced to WGS 1984 UTM Zone 31N (see Table 1).

**Elevation**

This condition is very important in identifying flood-prone areas since it controls the movement of overflow direction and the depth of water level (Stieglitz et al, 1997). The elevation distribution of the study was derived from the Shuttle Radar Topographic Mission (SRTM). In Fig. 2(a), the lowest elevation (< 120m) is found downstream while the upstream possesses higher elevations (> 450m). Since the flow of water is expected from upstream to downstream, the lower elevations are designated to be zones with the highest risk of flood hazard whenever extreme events occur.

**Drainage Density**

Drainage density is referred to the total length of all streams and rivers in a drainage basin divided by the total area of the basin (Oyegoke and Ifeadi, 2007). It determines how well or poorly a basin river channels drain. The flow of water within the streams can be determined by the drainage density. Drainage density reveals the level of infiltration and permeability of any drainage basin and can predict the rate and possibility of a potential flood. Firstly, the SRTM DEM was sink-filled to ensure proper basin and stream delineation, else derived drainage network may be discontinuous. After that, flow direction was generated using the Flow direction tool under Spatial Analyst in ArcGIS with the filled DEM as the input. Next is the creation of Flow Accumulation from which a threshold was generated using a conditional statement. Both flow direction and the threshold raster from the flow accumulation serve as input to deriving Stream Order in ArcGIS (ArcToolbox > Spatial Analyst Tools > Hydrology > Stream Order). The drainage density was generated using stream to feature as input. The drainage point value was generated from DEM, and then the drainage point was converted to 'stream to feature' to generate drainage density (Fig. 2b).

### Distance to river

Generally, areas close to rivers are susceptible to flooding in any river basin. Due to the downward flow of water from upstream to downstream, water tends to accumulate within most water bodies at lower elevations. These water bodies such as rivers, ponds, dams, and lakes are likely to exceed their capacities and hence cause flooding at a few distances depending on the terrain conditions. Because the distance to the drainage network is so important for flood mapping and regarded as one of the most influential factors (Fernández and Lutz 2010), we buffered from 1 to 5 metres to the river channel using buffer tools in ArcGIS as shown in Figure (2c).

### Soil

One of the most important variables that contribute to flooding is soil, which is defined as the topmost layer of the earth's surface. The qualities of the soil can be determined by the water retention capacity of the soil, which can assist in determining whether or not an area is prone to flooding. The amount of infiltration and runoff limit in any geographical area is determined by the soil type in that area. Soil information for the study area was extracted by clipping the area of study, and the global soil data downloaded from the FAO's website (Fig. 2d).

### Land use land cover (LULC)

Change in LULC has a significant influence on the flow of water on the surface. The increasing rate of urbanisation reduces the infiltration of water in the soil, thereby increasing the rates of runoff and subsequently flooding (Mahfuzur et al., 2021). The land use/land cover map of the basin area was derived from Landsat-8 OLI using ArcGIS 10.5. It was done using Maximum Likelihood supervised classification, by grouping the imagery into smaller classes based on their reflectance. Training samples were picked randomly from the Landsat imagery. Impervious surfaces are mostly found in urbanized and industrialised areas and restrict water infiltration, encouraging high-rate runoffs as compared to agricultural areas which encourage infiltration, reduced surface runoff and reduced flooding possibility (Fig. 2e).

### Slope

This is the degree of steepness and flatness of a geographic area. Slope possesses a great influence on flood mapping significantly as it indicates the rate, direction and duration of runoff and subsurface drainage. Slope determines the elevation of areas in distinct classes and, as a result, places that are easily inundated by floods. Runoff moves slowly on flat surfaces (low-slope), and consequently, more water is accumulated, so flat surfaces are more prone to flooding compared with steep surfaces (high slope). The length and steepness of the topography decrease the runoff, causing high infiltration within the area thereby resulting in water logging conditions. Areas with steep slopes show high peak discharge as compared to the low-lying area and cause the depletion of the storage in the upstream areas. The slope was created in the GIS environment using the spatial analyst tool of the arc-tool box and the slope command, with the input raster being the filled SRTM DEM. From analysis, 76% of the total area range from mild step to flat surface and indicates a high level of flood-prone characteristics (Fig. 2f).

#### 2..2.2 Raster Classifications and Ranking

To ensure an accurate ranking of factors, each flood contributing factor must bedivided into several classes. Raster layers were reclassified into five classes. LULC was reclassified into five basic classes (Water body, settlements, vegetation, outcrops and Bare surface) the other criteria used were reclassified into five basic classes (Very low, Low, Moderate, High and Very high). The classification was done on the criteria used to get their susceptibility to flooding vulnerability. with values ranging from 5 to 1, where the value of 5 denotes the most suitable and value 1 denotes the least suitable, for all factors and constraints considered. In this study, elevation less than 120m was assigned a ranking value of 5 (highly susceptible), low elevation with 130-250m was assigned 4, elevation of 260-340m was assigned 3, 350-440m was assigned 2 and extremely high grounds above 450m assigned value 1 (less susceptible). Slope was assigned ranking values from the lowest slope gradient to the highest slope gradient, ranging from 5 to 1 respectively. LULC was reclassified into 5 classes: settlements, water bodies, outcrops, bare land and vegetation (shrubs, grass and vegetated forest). For the drainage density, areas with very low drainage density were ranked as 1 and those with very high drainage density were ranked with a value of 5 while the distance to the stream of this study area, which ranges from 1–5 meters was reclassified to 5 meters (Very Low), 4 -5meters (Low), 3–4 meters (Moderate), 2–3 meters (High) and 1–2 meters (Very High) in order of their susceptibility to flooding. Clay soil is the most dominant soil type in the study area and has a very low infiltration rate, leading to high runoff in most cases.

## 2.2.3. Analytical Hierarchical Process (AHP)

The mapping weight or importance of each factor was determined using AHP. It is a method of representing the decision at hand in an organized way. It is made up of an overarching objective, a set of options or alternatives for achieving the goal, and a set of elements or criteria that link the options to the goal. In the modelling of the final hazard areas, the variables do not all play the same function or have the same weight. In this study, each factor was weighted using a pair-wise comparison method, which is one of the components of AHP, to define its relevance. Saaty's pair-wise comparison table was utilized to aid in the weighting of the pair-wise matrix with a consistency ratio (CR) of 0.004, which is less than 0.1 and thus provides an acceptable and sufficient process for identifying the impact of each criterion on floods (Table 2). This study made use of the percentages of influence of the criteria as inputs to a weighted overlay to derive the flood hazard (Table 3).

Table 2
AHP Decision matrix

| Factors | Elevation | Drainage density | Distance from river | Soil type | LULC | Slope |
|---|---|---|---|---|---|---|
| Elevation | 1 | 1.00 | 1.00 | 4.00 | 5.00 | 3.00 |
| Drainage Density | 1.00 | 1 | 1.00 | 2.00 | 4.00 | 1.00 |
| Distance from river | 1.00 | 1.00 | 1 | 3.00 | 3.00 | 2.00 |
| Soil type | 0.25 | 0.50 | 0.33 | 1 | 4.00 | 1.00 |
| LULC | 0.20 | 0.25 | 0.33 | 0.25 | 1 | 0.20 |
| Slope | 0.33 | 1.00 | 0.50 | 1.00 | 4.00 | 1 |

Table 3
**Weighted Overlay**

| S/n | Factor | % Influence | Value | Ranking | Vulnerability |
|---|---|---|---|---|---|
| 1. | Slope | 13.8 | 0-2.4 | 5 | Extremely |
| | | | 2.35–5.68 | 4 | High |
| | | | 5.69–10.36 | 3 | Moderate |
| | | | 10.37–18.72 | 2 | Low |
| | | | 18.73–85.25 | 1 | Very low |
| 2. | Soil | 10.8 | Sandy loam | 2 | Low |
| | | | Sandy clay loam | 3 | Moderate |
| | | | Loamy soil | 4 | High |
| | | | Clay | 5 | Extreme |
| | | | No data | 1 | |
| 3. | LULC | 4.6 | Water body | 4 | High |
| | | | Vegetation | 2 | Low |
| | | | Settlements | 5 | Extremely |
| | | | Outcrops | 1 | Very low |
| | | | Bareland | 3 | Moderate |
| 4. | Drainage density | 19.9 | < 16 | 1 | Very low |
| | | | 17–31 | 2 | Low |
| | | | 32–47 | 3 | Moderate |
| | | | 48–63 | 4 | High |
| | | | > 64 | 5 | Extremely |
| 5. | Distance from river | 23.0 | 0-0.082 | 5 | Extremely |
| | | | 0.083–0.16 | 4 | High |
| | | | 0.17–0.25 | 3 | Moderate |
| | | | 0.26–0.33 | 2 | Low |
| | | | 0.34–0.41 | 1 | Very low |

| S/n | Factor | % Influence | Value | Ranking | Vulnerability |
|---|---|---|---|---|---|
| 6. | Elevation | 28.3 | < 120 | 5 | Extremely |
| | | | 130–250 | 4 | High |
| | | | 260–340 | 3 | Moderate |
| | | | 350–440 | 2 | Low |
| | | | > 450 | 1 | Very low |

# 2.3 Hydrological Modelling in HEC-HMS

# 2.3.1 Data preparation and inputs

The surface discharge of the Osun River Basin was simulated using the Hydrologic Modeling Systems (HEC-HMS) model with historical daily rainfall (mm) data from the Tropical Rainfall Measuring Mission (TRMM) websites from 1981 to 2021. The Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) with a resolution of 30 m was obtained from the archives of the United States Geological Survey (USGS). Physical features of the catchment and basin parameters were extracted from the obtained DEM.

# 2.3.2. Model Set up

From the 30 m resolution DEM, the Geospatial Hydrologic Modeling Extension (HEC-GeoHMS), a geospatial hydrology tool, was utilized to produce all of the hydrologic input files required for hydrologic modeling in the HEC-HMS hydrological model (Hamdan et al., 2021). The HEC-GeoHMS was used to perform spatial analysis of the basin, DEM pre-processing, and stream and subbasin delineation. The following four (4) files were generated: a background map, a lumped basin model, a grid-cell parameter file, and a distributed basin model. In the HEC-HMS model, the basin is conceptually represented as a network of subareas connected by channel linkages. The HEC-HMS model setup is comprised of three key model components: the basin model, the meteorological model, control specifications, and time-series data (Đuki´c and Eri´c, 2021). The simulation system was configured in HEC-HMS after acquiring all of the primary data for simulation. The system includes rainfall losses (Soil Conservation Service (SCS) curve number), runoff transform (SCS unit hydrograph), analysis of meteorological data, open channel routing (Muskingum method), rainfall-runoff simulation, and parameter estimation (Ly, 2020). HEC-HMS computations were carried out in SI units.

# 2.3.3 Methods and Estimation of Parameters for HEC-HMS model

# 2.3.3.1 SCS Loss Method (Curve Number)

The Soil Conservation Service (SCS) curve number (CN) method was applied in this study to estimate rainfall losses/runoff volume. The curve number (CN), an index created by SCS, is commonly used to measure infiltration and surface runoff (Shukur, 2017). The Curve Number (CN) grid file, which is required to develop the HEC-HMS model, was obtained from the global CN database (GCN250) developed by Jaafar et al. (2019). The CN scale is 0 to 100. A CN value of 100 signifies surface water with zero infiltration. High CNs corresponded to regions with the highest potential for storm runoff, whereas low CNs corresponded to locations with minimal runoff but a high infiltration rate (Shukur, 2017). Major factors influencing CN include the hydrologic soil group (HSG), land cover type, treatment and management approaches, hydrologic condition, and antecedent runoff condition (Kumar and Bhattacharjya, 2020).

# 2.3.3.2 SCS Transform Method (Lag time)

The SCS unit hydrograph (UH) transform method was used to compute the transformation of runoff volume (rainfall excess) to discharge (US ACE, 2016). The UH method was used to determine the outflow at the specified outlet. This method requires lag time and impervious percentage of the watershed (Kumar & Bhattacharjya, 2020). Basin lag times for the sub-basins were calculated using Eq. (1) and then converted to minutes when used with HEC-HMS.

$$Lag = \frac{(S+1)^{0.7} L^{0.8}}{1900 \times Y^{0.5}}$$

1

where S = maximum retention (mm), lag = basin lag time (hour), L = hydraulic length of the catchment (longest flow path) (feet) and Y = basin slope (%).

# 2.3.3.3 Routing— Muskingum Method

The Streamflow (channel) routing was determined using the Muskingum method. The Muskingum method was used to predict discharge at various sub-watershed outlets (Kumar & Bhattacharjya, 2020). The X and Y parameters are needed for the Muskingum technique. In the case of the meteorological component, the precipitation data input was spatially and temporally distributed over the Osun River Basin (Feldman, 2000). The spatiotemporal precipitation distribution was accomplished by the gauge weight method and daily precipitation input data was used.

# 2.3.3.4 Model Simulation

After the model components have been created and populated with data, the simulation run was created, and the model was run from 1981 to 2021 to determine the basin's discharge.

# 2.4 Descriptive statistics of river discharges

The annual peak discharge of the basin was subjected to statistical analysis to determine the mean, standard deviation, and coefficient of variation using MINITAB version 20 statistical software. The discharge frequencies analysis was carried out and the extreme (Maximum) daily discharge ($m^3/s$) of the basin from 1981 to 2020 was computed.

# 2.5 Flood Frequency analysis

The recurrence interval (RI)/return period (T) of the Osun River discharges was calculated using Eq. 2.

$$RI = \frac{n+1}{m}$$

2

where n = the number of flood data points used in the calculation, and m = the rank of that particular runoff/flood. In the study, the number of the sample dataset is 40 for the runoff events. The flood frequency curve was thereafter graphed by plotting the discharges against the recurrence interval.

# 2.5.1 Gumbel Method

Gumbel is a statistical distribution derived from extreme theory (Samantaray and Sahoo, 2020). It is widely used for the probability distribution of extreme values in hydrologic and meteorological investigations for forecasting peak flows, maximum rainfall, and other weather-related events (Gulap & Gitika, 2019).

The required return period (T) has been calculated using Eq. (2) above.

Then, the mean ($\mu$) and standard deviation ($\sigma_{n-1}$) of the discharge data was determined. Further, the abridged mean ($Y_n$) and abridged standard deviation ($S_n$) were determined from Gumbel's extreme value distribution Table for the given sample size (n).

The abridged variate ($Y_T$), a function of a given T is given by

$$Y_T = -\left[ln.\, ln\frac{T}{T-1}\right]$$

3

The frequency factor (K) is expressed as follows in Eq. (4);

$$K = \frac{(Y_T - Y_n)}{S_n}$$

4

Thus, the predicted maximum flood discharge ($X_T$) corresponding to the respective return periods is computed using the standard normal distribution formula (Eq. 5):

$$X_T = \mu + K\sigma_{n-1}$$

5

The flood discharge at return periods of 10, 20, 30, 50 and 100 years was estimated using Gumbel's extreme value distribution.

# 3. Results And Discussion

## 3.1. Potential flood hazard zones

Knowledge of the potential flood zone of an area is key to future mitigation and adaptation plan. It provides policymakers and community information about the potential risk zones that require evacuation during flooding, relocation and financial investments for disaster risk reduction. Figure 3 shows the potential flood hazard zones of the study area, derived from the multicriteria analysis. Flood hazard risk potentials were categorised into three (3); the extremely high, and moderate low hazard zones. About 7% of the area covered is in the low hazard zones while 11% of the area is at high risk of flooding and the moderately prone zones cover a larger area of 82% of the Osun River basin (Fig. 4). It is clearly shown that several parts of the Osun-river basin are moderately vulnerable to floods. Generally, flood threats are found in low-elevation areas, according to the study. This can be attributed to the fact that water flows from higher elevations to lower elevations, and thus concentrate more on lower slopes. The study confirms the significance of the influence of topography and slope on flood susceptibility. Therefore, areas of lower elevation must be given special consideration and as much as possible excluded from compact infrastructural development in land use planning. This will reduce the concentration of valuable properties within the floodplain and subsequently reduce the risk level. It should be noted that, although the percentage in the critical (high) zones is lower compared to the moderately prone zones, future land-use and climate changes can impact greatly on these zones, hence they could be more susceptible to flooding.

## 3.2. Hydrological trends in the Osun River basin

Figure 5 showed the annual peak discharge from 1981 to 2020 in the basin. The "annual peak discharge" is the maximum discharge observed in the basin for a given water year. Considering the flood for the entire period of 40 years from 1981 to 2020, it was found that the maximum peak daily discharge was recorded on 25th July 2007 while the minimum peak daily discharge was recorded on the 27th September 2003. The peak discharge for the simulation period ranged from 531.5 to 1846.8 $m^3/s$ (Fig. 5). The 2nd and 3rd largest discharges were recorded in the years 2009 and 1989, respectively, with flows of 1536.5 and 1328.8 $m^3/s$. The annual peak discharge from 1981 to 2020 in the basin has a mean value of 915.4 (± 241.15) $m^3/s$ with a variability of 26%.

## 3.3. Peak discharges and flood frequency: Implication of flooding

A set of historical data was used to calculate the recurrence interval of the historical simulated flood discharge. The recurrence interval of annual peak discharge represents an estimation, based on the historical record, of the probability of a given flood discharge occurring over a given period (Meigh, 1995). The flood frequency curve shows the probability of the occurrence of the given discharge event for the 1981 to 2020 period (Fig. 6). Examining the frequency analysis (Fig. 6), the peak discharge (1846.8 $m^3$/s) at the basin has a 41-year recurrence interval. This means there is a 1 in 41 chance that a streamflow of 1846.8 $m^3$/s or more will occur during any year at the basin discharge-measurement site. Thus, a peak flow of 1846.8 $m^3$/s at the basin is said to have a 41-year recurrence interval. Using Gumbel's extreme value distribution method, the calculated discharge flood lies within 1117.43 $m^3$/sec to 1858.51 $m^3$/sec for 5 years to 150 years return period for the Osun River basin. The estimated flow discharges for return periods of 10, 20, 30, 50 and 100 years, respectively, are 1117.43, 1275.99, 1428.09, 1515.58, 1624.96, 1772.48, and 1858.51 $m^3$/sec. In Nigeria, several extreme flood events have been recorded, and they are quickly becoming annual occurrences, mostly in the form of coastal, flash, and urban floods (Komolafe et al., 2020a; 2020b; Olokeogun et al. 2020). In recent years, floods with catastrophic consequences have occurred across the country (Komolafe et al., 2020a; 2020b; Olajuyigbe et al. 2015; Olorunfemi et al., 2020). Stream flow forecasting is required for a variety of reasons, including water resource planning, strategy development, manoeuvre and maintenance events (Samantaray and Sahoo, 2020). These estimates are critical for the design and operation of flood control structures (dams, retaining basins), infrastructure items (flood defenses, bridges, roads, and dams), as well as flood hazard management, planning, flood hazard mapping, and improving warning methods across a region (Leeen and Dolinaj, 2019; Kjeldsen et al., 2014; Javelle et al., 2010).

# 4. Conclusion

Flood risk assessment and estimation of the peak discharge and runoff volume are the important steps in flood management and control, design of hydraulic structures, watershed management, and formulation of reservoir operation policies, among others. In this study, the multi-criteria analysis (MCA) was carried out to determine the flood risk zones in varying intensity, for the Osun River Basin area, Nigeria. Surface discharge for the Osun River basin was simulated using the Hydrologic Modeling Systems (HEC-HMS model) using historical daily rainfall data from 1981 to 2020. Several parts of the Osun-river basin are moderately vulnerable to floods. The study found that flood threats are more prevalent in low-elevation areas because the water flows from higher elevations to lower elevations, concentrating more on the lower slope. Topography and slope have a significant effect on flood susceptibility. Areas of lower elevation should be given special consideration and as much as possible excluded from compact infrastructural development in land use planning. Although the percentage in the critical (high) zones is lower compared to the moderately prone zones, future land use and climate change can impact greatly on these zones, hence they could be more susceptible to flooding. The peak discharge for the simulation period ranged from 531.5 to 1846.8 $m^3$/s. The peak discharge (1846.8 $m^3$/s) at the basin has a 41-year recurrence interval. Thus, a peak flow of 1846.8 $m^3$/s at the basin is said to have a 41-year recurrence interval. Using Gumbel's extreme value distribution method, the calculated discharge flood lies within 1117.43 $m^3$/sec to 1858.51 $m^3$/sec for 5 years to a 150-year return period for the Osun River basin. These estimates are critical for the design and operation of flood control structures (dams, retaining basins), infrastructure items (flood defenses, bridges, roads, and dams), as well as flood hazard management, planning, flood hazard mapping, and improving warning methods across the study region.

# Declarations

<u>**Author Declarations**</u>


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**Conflict of Interest:**

Authors declare that there is no conflict of interest

**Consent to participate**

All Author's consent were sought for and agreed to participate in the research

**Consent for publication**

Authors consented to publish the study reputable journal

**Author's Contribution**

A.A.K. conceptualized, structured and wrote the manuscripts; I.E.O and C.C.O. carried out analysis and wrote the main manuscript text and O.O.P reviewed and edited the manuscript. All authors reviewed the manuscript.

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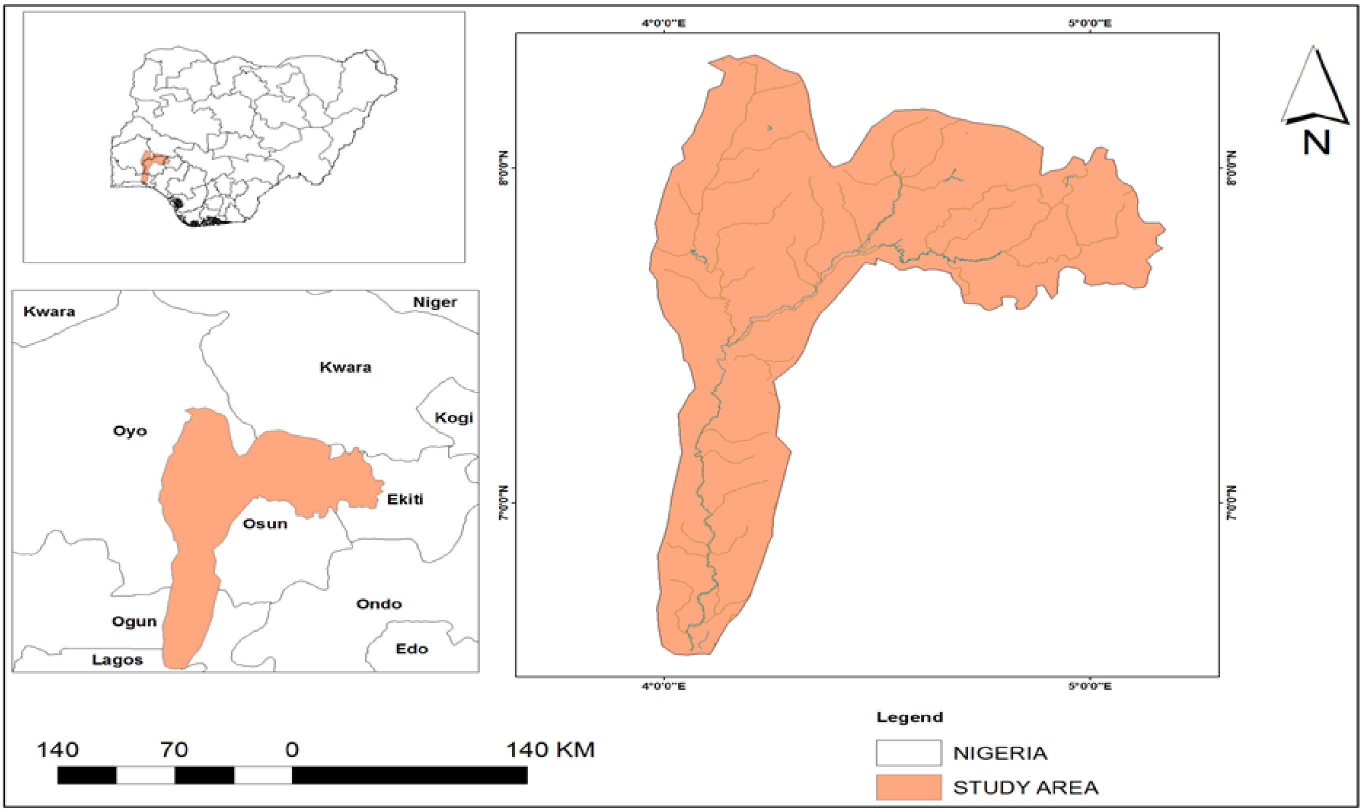
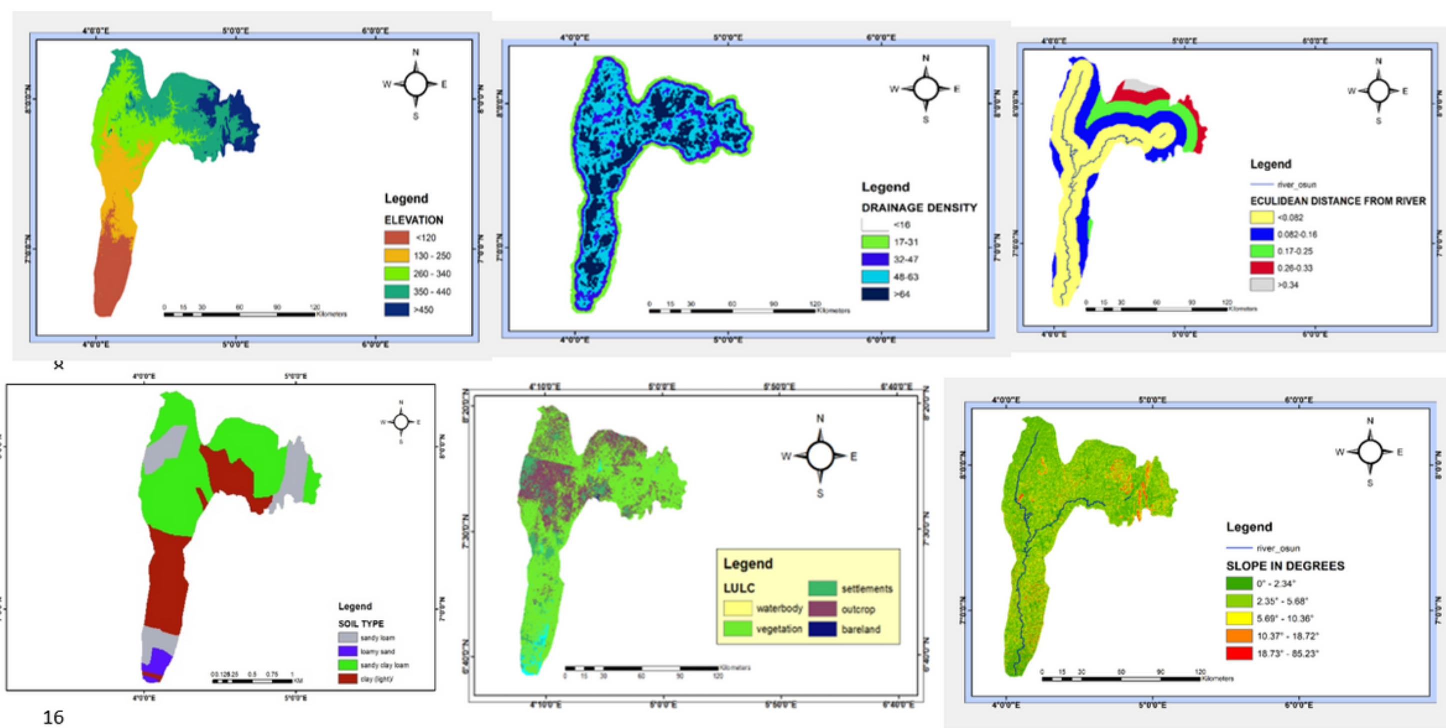
## Figures




## Figure 1

Study area location




## Figure 2

Six factors used in the multi- criteria analysis: (a) elevation; (b) drainage density; (c) distance from the river; (d) soil type; (e) land use/land cover; (f) slope

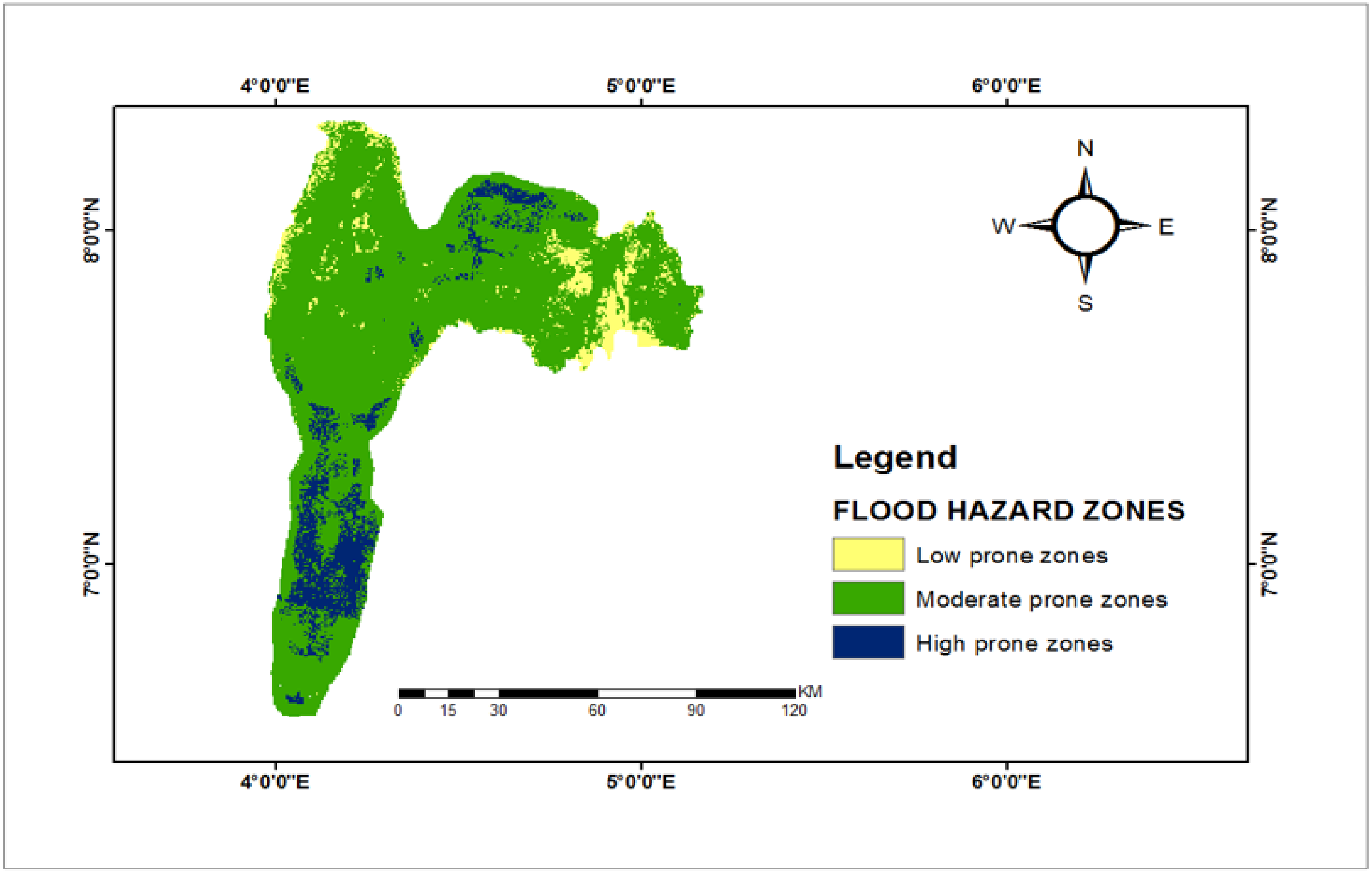
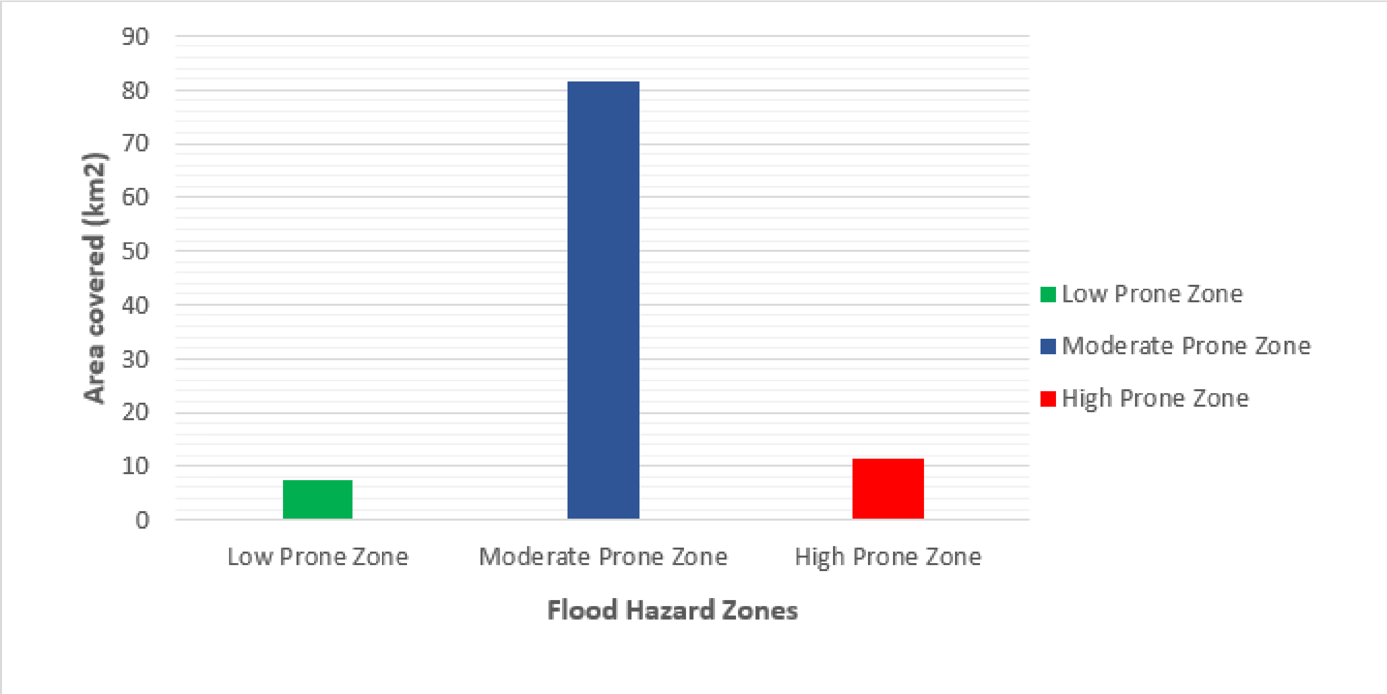


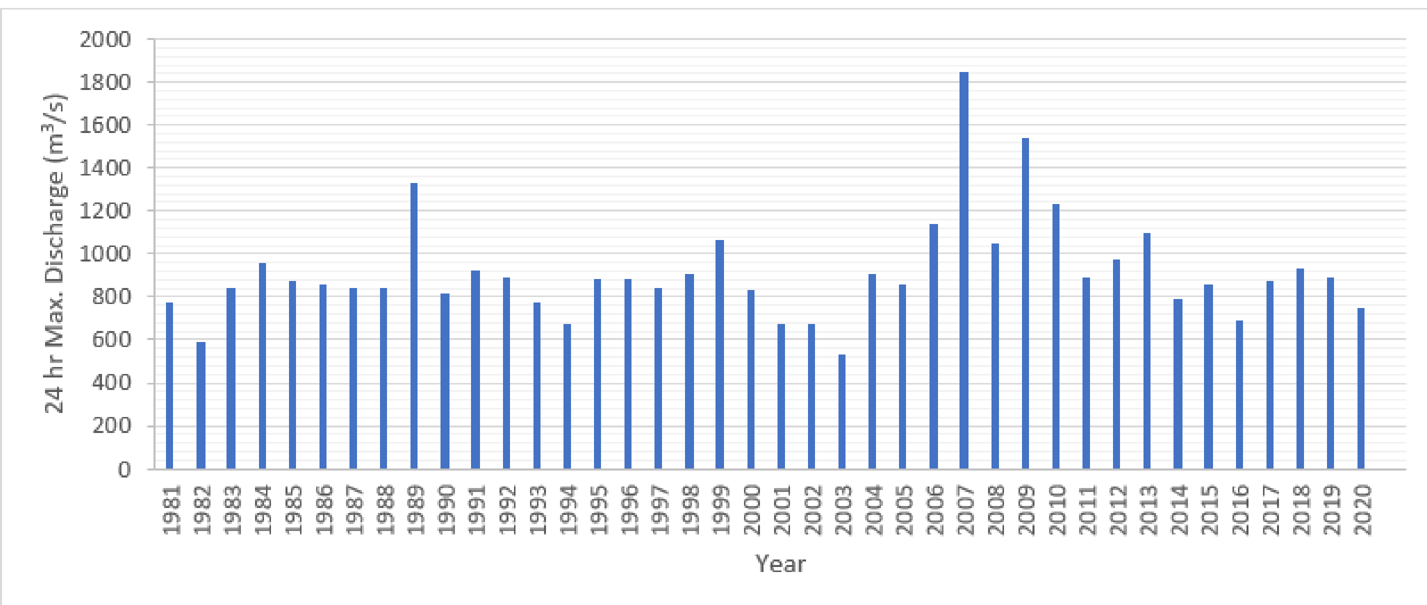

**Figure 3**

Multi-criteria flood hazard map of the river basin



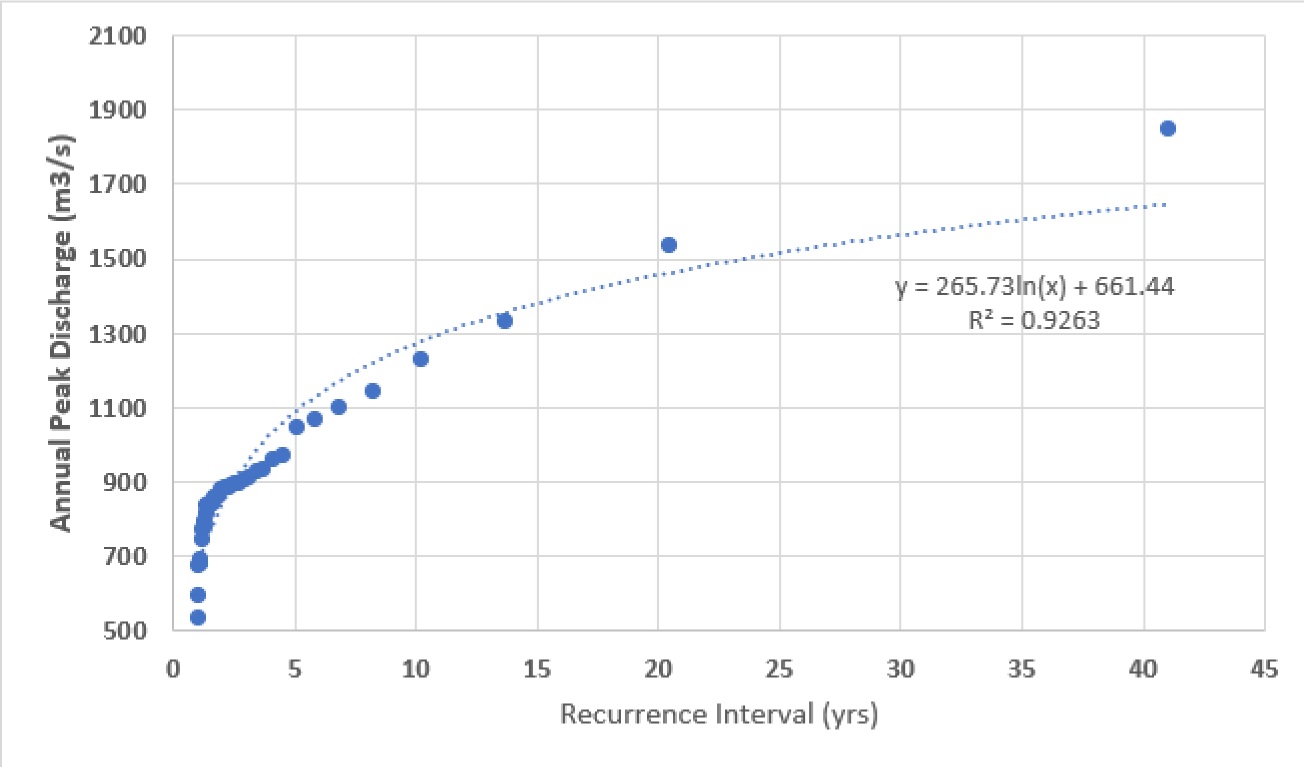

## Figure 4

Relative distribution of flood hazard zones in the basin using MCA




## Figure 5

Peak (extreme) discharge ($m^3/s$) of Osun basin from 1981 to 2020




## Figure 6

Flood frequency curve for the 1981 – 2020 period using Gumbel's Extreme Value Distribution Method