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Spatial analysis of flood risk zones in Osun State, Nigeria

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Abstract

The study assessed the spatial analysis of flood risk zones in Osun State, Nigeria. The study made use of landuse/land cover data, elevation data, soil types and flood dates to compute the flood risk zones in Osun State, Nigeria. Descriptive statistics were applied for the study. Findings showed that in 2017, flood was detected in 16 LGAs of the state, comprising Iwo, Egbedore, Bolorunduro, Boripe, Ife North, Aiyedire, Ejigbo, Ila, Irepodun, Irewole, Isokan, Odo-Otin, Ola Oluwa, Osogbo LGAs which were 13 in number. These increased to 30 LGAs in 2023. Some towns identified included Esa Oke, Oranran, Bode Osi, Ode-Olowo, Ajebandele, Olode Ifon, Modogbon, Aketa and Ikoyi. Between 2017 and 2018, flood extent increased from 0.076 sq. km to 0.078 sq. km while in 2019, a marked increase of 0.293 sq. km was discovered and in 2023, it was 1.348 sq km. between 2017 and 2023, central and western LGAs such as Osogbo, Ede North, Ede South, Ife Central, Iwo, Isokan, and Aiyedire emerged as flood recurrent hotspots due to low-lying terrain, urbanization, and poor drainage. Eastern LGAs such as Oriade, and Obokun were less affected due to higher elevation and vegetation cover. Moreover, annual flood-impacted LGAs increased with increasing time. Similarly, the flooded area increased from 2017 to 2023, exposing the weakness of current structural measures under extreme rainfall. The study thus recommended that the government should enforce floodplain zoning that can restrict high-density settlements in very vulnerable zones; adopt nature-based solutions which can protect wetlands and expand urban green spaces for natural water retention; and control land use expansion to implement urban containment policies to limit impervious surface growth.

Keywords: Flood; Urbanization; Hotspot; Risk; Annual

1. Introduction

Flooding according to Gobo (2019) in Nigeria is a significant environmental challenge, exacerbated by climate change and increasing rainfall variability. Nigeria's diverse terrain, which includes coastal plains and highlands, has made flood dynamics more complicated. In the Niger Delta region, heavy downpour and poor drainage systems regularly lead to severe flooding, impacting communities and damaging infrastructure (Nwilo et al, 2018). Furthermore, flood risk downstream is exacerbated by upstream release of dams such as Kainji and Lagdo. The effectiveness of flood management in Nigeria therefore, requires a wholistic understanding of these factors, people oriented strategies as well as environmentally friendly practices to mitigate the enormous impact of flooding in urban and rural areas alike (Gobo, 2019). In Osun State, the adverse effect of flooding is unprecedented, due to the region's distinct hydrological and topographical features (Adelekan, 2010). As a result of these factors, it is unquestionably vulnerable to flooding, necessitating the development of more robust and effective flood management technique (Opolot, 2013).

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The introduction of Remote Sensing (RS) and Geographic Information Systems (GIS) has brought about a mindset shift, in the field of disaster management, particularly in flood prediction and risk assessment. With the use of RS timely and accurate spatial data from satellite imagery, are accessible, while GIS provides effective tools for data integration, analysis, and visualization in the GIS environment (Ding et al., 2021).

Recent developments in RS and GIS have produced complex models that can model flood scenarios, forecast flood levels, and evaluate a region's susceptibility to future floods. This is because they offer vital information for making well-informed decisions on infrastructure construction, land use planning, and budget allocation for flood mitigation. These models are extremely helpful to policy makers, flood control experts as well as urban planners (Hagos et al., 2022).

Flooding in urban areas is both a complicated and multifaceted challenge that threatens public safety, infrastructure, and environmental sustainability. In Osun State, this challenge is worsened by rapid urbanization, inadequate drainage infrastructure, and the ever growing impact of climate change. These are contributing factors to the increase in the frequency and severity of flood events, leading to significant risks to the state's socio-economic development and the well-being of its residents (Adelekan, 2010; Ologunorisa & Abawua, 2005). Increases in impermeable surfaces brought about by rapid urban expansion, intensify surface runoff and decrease natural infiltration. In addition, a good number of urban areas in developing nations, have inadequate drainage systems incapable of handling rainwater sufficiently, which increases the risk of flooding (Akobo, 2005; Amangabara et al., 2008; Teme & Gobo, 2005).

Significant flood disasters have occurred in Osun State in recent times, and it always leaves the residents with tales of woes. These incidents have necessitated the need for an all-encompassing and real time framework for flood risk assessment that makes use of RS and GIS capabilities. Researchers can produce detailed flood hazard maps and conduct risk assessments by utilizing sophisticated RS techniques, such as multispectral, radar, and LIDAR technologies, alongside with GIS-based multi-criteria decision analysis (Ologunorisa & Tersoo, 2006). Irrespective of the efforts by state authorities to mitigate flooding, recurrent flood events continue to endanger the lives of the residents, damage to property, and disrupt the economic activities taking place in the area. Natural elements like terrain and hydrology, as well as human impacts like shifting land uses and poor urban planning and inadequate waste disposal, combine to create Osun State's complicated flood dynamics (Ojo, 2021). Recent research has demonstrated the study area's growing susceptibility to flood disasters, which is made worse by changes in land use, urbanization, and climate change (Ashaolu, 2017). As the region continues to face the difficulties brought on by its physical and geographic features, there is a clear need for efficient urban management and disaster preparedness (Gasu & Odusola, 2021). Thus, the present study assessed the flood risk zones in Osun State, Nigeria.

2. Materials and Methods

The study was carried out in the entire Osun State. Osun State which is in the western part of Nigeria is the focus of this study. The geographical coordinates of Osun State are: Latitude: 7.0° to 8.0° North, Longitude: 4.0° to 5.5° East (Osun State Government, 2023).The area covers approximately 9251 square kilometers and it is bounded by Ogun State to the south, Kwara State to the north, Oyo State to the west, and Ekiti and Ondo States to the east. The study area is landlocked yet rich in water resources, with the notable River Osun flowing through the city, which is a vital source of water and cultural heritage for the inhabitants (Osun State Government, 2023). The geography of the study area consists of a mixture of lowland forests and a drier Guinean forest-savanna mosaic in the north. The city is more susceptible to floods as a result of its varied terrain, particularly during the rainy season. The Köppen climate categorization classifies Osun State into the Tropical Monsoon (Am) and Guinea Savanna (Aw) climatic zones (Ashaolu, 2017). The region has a dual rainfall trend, with two different maxima in June-July and September-October. The tropical climate zone in which Osun State is located is distinguished by distinct rainy and dry seasons. Rainfall peaks in the month of June; during the rainy season, which normally lasts from April until October. The weather is influenced by harmattan winds throughout the dry season, which runs from November to March. Temperatures range from 21°C to 34°C, and there is roughly 1,500 mm of rainfall on average every year. The movement of the Inter Tropical Convergence Zone (ITCZ) and the harmattan winds from the Sahara Desert has an impact on the city's climate (Climate-Data, 2023). The basement complex geological formation, which influences the distribution and availability of groundwater resources, is what defines the hydro-geology of the study area (Ifabiyi, 2005). Rainfall is the main source of replenishment for groundwater resources in this region, although urbanization and climate change have impacted the rate of replenishment. Climate change has not had a significant effect on groundwater supplies in the studied area, despite the fact that it can increase runoff and possibly cause more extreme flooding occurrences, according to studies. A major body of water that flows through the city, the River Osun is essential to the hydrology of the region and supplies water for industrial, agricultural, cultural, and residential purposes (Ifabiyi, 2005 ; Adeyemi, 2019).

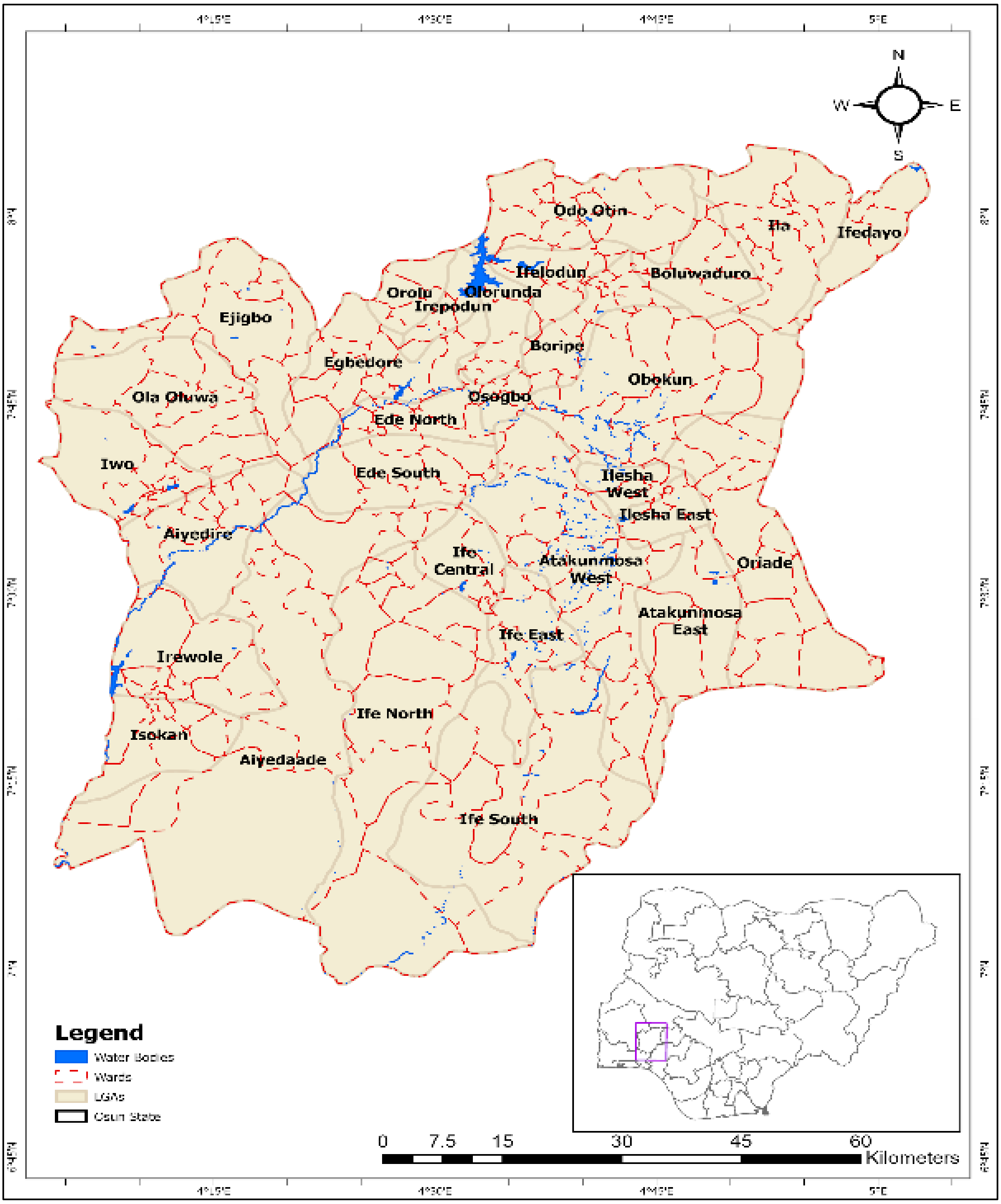

Figure 1 Map of the Study Area

The topography of Osun State is moderately undulating, with elevation ranging from about 66 meters in the southern lowlands to around 733 meters in the northeastern highlands. The terrain generally rises from southwest to northeast, forming three main zones: the southern lowlands (below 150 m), the central undulating plains (150–300 m) with scattered inselbergs, and the northern highlands (300–733 m) marked by hills and ridges underlain by Basement Complex rocks. These variations in relief strongly influence drainage, runoff, and flood susceptibility across the state (Adefisan & Akinbobola 2014). The state's hydrological network is dominated by several major rivers, including the Osun River, which traverses the state for approximately 120 km, as well as the Oba, Erinle, and Oyan Rivers. These rivers are part of the larger Niger River basin and serve as the main drainage outlets for surface and storm water (Osun State Government, 2018). The peak flow periods for these rivers typically occur in August and September, with discharge values reaching between 120–150 m^3/s, especially at monitoring points such as the Osogbo gauging station. The base-flow period generally spans from February to April, when discharge rates drop to 15–20 m^3/s. These seasonal flow variations directly influence the extent and frequency of flood events, particularly in low-lying and poorly drained areas (Osun State Government, 2018). Several critical flood hotspots have been identified across the state. For example, Ayetoro in Osogbo has experienced five or more flood events since 2015, primarily due to poor drainage, channel obstruction, and increasing urban runoff (Alimi et al. 2022). Similarly, several other communities across the state including Ifon, Ede, and Ilobu have also experienced severe flood events, resulting in widespread property damage and substantial livelihood losses (Alimi et al, 2022).

Flood dates are one of the key datasets for this study; documented flooding dates served as a precursor for dataset acquisition, particularly the Sentinel 1 and 2 Imagery datasets and the climatic/biophysical datasets. This information was validated using publications and social media post from verified handles. The flood date was used to derive flooding and the local government areas were used to validate affected locations. A total of 14 flood dates were acquired from 2017 to 2023 with most years having more than one flood incidence. Osun State is traversed by several major rivers, including the Osun River, Oba and Erinle Rivers (Ogundolie et al, 2024). These rivers exhibit distinct flow regimes, with peak discharge rates occurring between August and September, reaching up to 150 m^3/s at the Osogbo gauge station. Base-flow conditions are typically observed from February to April, with flow rates ranging from 15 to 20 m^3/s (Adewumi et al., 2022).

Critical flood-prone areas in Osun State include Ayetoro in Osogbo, which has experienced recurrent urban flooding, with significant events occurring in 2015 and 2016 (The Nation, 2016). Similarly, Gbongan has witnessed agricultural land inundation in recent years, notably in 2020 and 2022 (Daily Post, 2021). Sentinel-1 Synthetic Aperture Radar (SAR) imagery data is a satellite whose sensors operate in the C-band. The C-band has low susceptibility to atmospheric interference which makes it ideal for flood detection compared to Optical instruments which produce unusable images in heavy rains due to cloud cover. Sentinel 1 imagery was acquired for dates corresponding to the flood dates above. Imagery from optical sensors are not optimal for flood detection even with spectral indices like Normalized Difference Water Index (NDWI) or Modified Normalized Difference Water Index (MNDWI) due to cloud cover which are pervasive in Multi-spectral imagery, especially at the time of the year when the floods were recorded (between August to November). However, imagery from optical sensors (Sentinel-2) was used for land cover classification which have uses at different stages of the modelling process. Different land cover types have different susceptibility to flooding; built up areas for example are flood prone due to poor drainage systems, while forests have more arable soils and as such are less likely to be heavily impacted by flooding. To model flood risk and vulnerability, several environmental, climatic and geological parameters which are drivers of flooding were identified. These were used as explanatory/independent variables to model the recorded flooding and develop a risk evaluation identifying areas which will be susceptible to flooding in future dates. Exploratory variables include rainfall, evapotranspiration, soil moisture, atmospheric temperature, humidity, atmospheric pressure, surface runoff amount and subsurface runoff amount. These data were obtained from NASA Land Processes Distributed Active Archive Centre (LP DAAC).

From the flood date acquired from the Ministry of Environment (2017-2023), sentinel 1 imagery were acquired for same dates and for non-flood dates. An identified water body in the state (Owala lake) was also extracted as a sample of water body for flood detection analysis carried out in ArcGis Pro. The overall methodology adopts a bottom-up approach, which is to understand the climatic, environmental and geographical characteristics of the study location which were influential in the flooding. Flood dates were acquired for a period which spanned 7 years (2017 – 2023). Over this period, a total of 14 flood event dates were used for this research as provided by the Ministry of Environment which impacted major towns in the Table 1.

Three Sentinel-2 tiles were required for full coverage of the study area: 31NGJ, 31NFJ and 31NFH. Each year, Imagery data was acquired for Late December (between the 21st and 31st of December) due to low cloud cover. The Level 2A dataset was used for this study which had been processed to the Bottom of Atmosphere Surface reflectance. Each band of the visible and Infrared bands (including Near Infrared and Shortwave Infrared) were downscaled, stacked, mosaicked and clipped to the geometry of the Osun state boundary.

The Maximum Likelihood algorithm was used to carry out Supervised Land cover classification, to derive the land cover classes. The target of this classification is the identification of 5 major land cover types which include built-up areas (developed), bare ground, cropland and primary vegetation. These land cover types are categorical and as such cannot be used directly to model flood risk and flood water permeability. To use Land cover data for flood risk modelling, the land cover data were reclassified based on their permeability to remove flood water from the surface. Urban areas will have the lowest permeability while vegetation areas will have high permeability rating values. The land cover data has additional utility in flood detection, pixel values of known water bodies, (rivers, lakes etc) was used to identify water bodies in the flood detection. For this study a sample of the Owala Lake was extracted to be used as a mask.

Table 1 Flood dates

S/N	Flood Date	Baseline Date
	09/04/2017	08/15/2017
	08/01/2018	07/12/2018
	08/20/2019	30/7/2019
	09/01/2019	
	08/07/2020	12/09/2020
	21/08/2021	04/18/2021
	28/09/2021	
	29/10/2021	
	29/11/2021	
	24/07/2022	8/21/2022
	10/09/2022	
	14/10/2022	
	12/06/2023	5/23/2023
	11/07/2023	
	24/07/2023	

Typically, 2 – 4 Sentinel -1 GRD images provide full coverage of the AOI. These images were acquired, mosaicked and clipped for dates corresponding to the flood and baseline dates respectively. Further preprocessing was carried out on each image to get the final Analysis Ready Imagery dataset (ARD). These preprocessing steps included:

2.1. Conversion to Linear Representation

Sentinel-1 SAR (Synthetic Aperture Radar) data is often provided in decibels, (on a logarithmic scale). This raw form makes removal of speckles from the imagery difficult. The respective imageries are transformed to the linear values by dividing the 1st band of the imagery by a factor of 10. A constant image of value 10 is created and raised to the power of the transformed image.

$$I_t=10^I \quad \text{……………………………………………… Equ 1}$$

Where I_t is the image transformed to the linear scale from the logarithmic scale and I is the input image.

2.2. Refined Lee Filtering

A filtering algorithm removes speckles and noise from radar imagery. Noise and speckles are detrimental to radar imagery because they degrade imagery and make interpretation rather difficult. The Refined Lee is a derivative of the Lee method but offers improved functionality in that it can preserve prominent edges, linear features, point target, and texture information. The flood detection was based on identifying water bodies within the state and within the baseline image and on the image of the flood date. To achieve this, the Owala Lake mask extracted from the land use land cover was used to calculate the zonal statistics of a known water body in the transformed baseline image. The zonal statistics produced the mean and standard deviation statistics of the water pixels in the baseline data. These statistics values were used to determine threshold values for water body identification through the entire imagery (baseline and flood date imagery) using the mean standard deviation method as shown below.

$$u_t=M_m+2M_{sd} \quad \text{……………………………………… Equ 2}$$

$$l_t=M_m-2M_{sd} \quad \text{……………………………………… Equ 3}$$

Where U_t and L_t represent Upper and Lower thresholds respectively. M stands for the Mask zonal while m and sd represents the mean and standard deviation. By applying derived thresholds to the transformed baseline and flood date images, all pixel values that fall within the threshold are assigned a value of 1 and others are assigned a value of 0. The value 1 pixels represent water bodies in both natural occurring and flooded regions (in the case of the flood date image. All the following operations are carried out on Google Earth Engine. The masked image (with values of 0 and 1) for both the baseline image and flood date image are downloaded as a GEOTIFF raster for further processing in ArcGIS.

Furthermore, to detect flooded areas, image differencing was carried out on the exported GEOTIFF image. This produced a resultant raster with 3 possible values (-1, 0 and 1).

$$\Delta = MF_d - Mb_d \quad \text{.......... Equ 4}$$

From this image differencing, any overlapping pixels with the same value (0 or 1) will produce a value of zero. Pixels which had water (1) in the baseline but was missing (0) in the flood date mask (0) will have a resultant pixel value of -1 and finally any pixels with water (1) in the flood date mask but had a value of 0 in the baseline mask will produce a value of 1. This final scenario will be regarded as flooded areas while the first and second scenario was referred to as pixels with no change and drought (dried up water bodies. Using the conditional tool of ArcGIS's spatial analyst toolbox, these later pixel values were reassigned to a value of 0 with the value 1 pixels retaining their value.

As mentioned earlier, pixels with a value of 1 are flooded and 0 are not, however, false positive detected floods are possible. This is possible in known water bodies if large enough objects were within the baseline scene and not in the flood date image. To remove this artifact, the flooded pixels are extracted and converted to vector layers. Any flood vector parts which overlap water bodies are identified as false positives and removed.

This study also explored flooding events within a 7-year window. Additionally, a single pair (before and after flooding) of Sentinel-1 imagery was used to generate a recent digital terrain model (DTM) or digital surface model (DSM) of the AOI. The Elevation slope was also generated from the DSM/DTM. This is also an important variable because sloppy areas are likely to have higher runoff and as such are less prone to flooding compared to flat areas.

There is a worldwide climate dataset repository with spatial resolution of 0.1^0 and temporal resolution of three days, made available by the National Aeronautics and Space Administration (NASA) and National Oceanic and Atmospheric Administration (NOAA). Each collected climate parameter followed variable dependent aggregation. Variables such as surface temperature and air pressure were aggregated through averaging, whereas precipitation and surface runoff were aggregated by summation of each dataset cycle.

Like the elevation dataset, there is little variation in soil type over time. This implies that negligible to zero soil type changes are expected to occur over short periods of time. Generally, the FAO maintains a single soil type dataset which updates every few years. The last update was carried out in 2023 to version 2.0. This is the version that was used for this study. The soil data is also categorical data and was reclassified in terms of permeability to absorption and permeability. The data analysis for this study integrated both descriptive and inferential statistical approaches.

3. Results

The result shows that in 2017, flood was detected in 16 LGAs of the state, comprising Iwo, Egbedore, Bolorunduro, Boripe, Ife North, Aiyedire, Ejigbo, Ila, Irepodun, Irewole, Isokan, Odo-otin, Ola Oluwa, Osogbo LGAs. The map of flood risk zones from 2017 and 2023 are highlighted from Figure 2, Figure 3, Figure 4 and Table 1. Some towns identified included Esa Oke, Oranran, Bode Osi, Ode-Olowo, Ajebandele, Olode Ifon, Modogbon, Aketa and Ikoyi. Between 2017 and 2018, flood extent increased from 0.076 sq. km to 0.078 sq. km, suggesting relatively stable hydrological conditions. However, in 2019, a marked increase to 0.293 sq. km indicated a shift towards heightened flood susceptibility. A slight decline to 0.265 sq. km in 2020 suggests a temporary reduction in flood extent, potentially influenced by varying climatic conditions. In 2021, flood extent rose significantly to 0.466 sq. km, reflecting an intensification of flood events. Conversely, 2022 witnessed a decline to 0.139 sq. km. The most substantial increase occurred in 2023, with flooded land expanding dramatically to 1.348 sq. km, indicating a major flood event. Table 3 also showed Oriade LGA experienced the highest flood depth of 16m and 2869.258075 square meters in 2021, while Irewole, Ila and Ifedayo had the least flood depth of 1 metre each in 2018, 2019 and 2019 respectively (Table 3) while total number of 390,450 people were affected by flood in 2012, this number was reduced to 81,439 persons in 2018 (Figure 3). On the other hand, the number of LGAs affected by flood increased from 16 in 2018 to 30 in 2022 and 2023 (Table 2 and Figure 4).

Table 2 Flood Extent 2017-2023

Year	Flood Extent (km^2)	% Change from Previous Year	Notable Remarks
2017	0.076	Baseline	Reference year
2018	0.078	+2.85%	Slight increase
2019	0.293	+275.91%	Peak pre-2023
2020	0.265	−9.59%	Moderate decline
2021	0.466	+75.85%	Second-highest pre-2023
2022	0.139	−70.16%	Sharp decrease
2023	1.348	+870.10%	Unprecedented surge

Note: The 2023 flood extent is **17.7×** the 2017 baseline, showing a drastic escalation in flood risk severity.

Table 3 Flooded LGAs in the Study Area (2017-2023)

	2017	2018	2019	2020	2021	2022	2023
Affected Local Government Areas	Aiyedaade	Aiyedaade	Aiyedaade	Aiyedaade	Aiyedaade	Aiyedaade	Aiyedaade
	Aiyedire	Aiyedire	Aiyedire	Aiyedire	Aiyedire	Aiyedire	Aiyedire
	Boluwaduro	Atakunmosa West	Atakunmosa East	Atakunmosa East	Atakunmosa East	Atakunmosa East	Atakunmosa East
	Boripe	Boluwaduro	Atakunmosa West	Atakunmosa West	Atakunmosa West	Atakunmosa West	Atakunmosa West
	Egbedore	Boripe	Boluwaduro	Boluwaduro	Boluwaduro	Boluwaduro	Boluwaduro
	Ejigbo	Ede North	Boripe	Boripe	Boripe	Boripe	Boripe
	Ife North	Ede South	Ede North	Ede North	Ede North	Ede North	Ede North
	Ila	Egbedore	Egbedore	Ede South	Ede South	Ede South	Ede South
	Irepodun	Ife Central	Ejigbo	Egbedore	Egbedore	Egbedore	Egbedore
	Irewole	Ife North	Ife East	Ejigbo	Ejigbo	Ejigbo	Ejigbo
	Isokan	Ifelodun	Ife North	Ife Central	Ife Central	Ife Central	Ife Central
	Iwo	Ila	Ifedayo	Ife North	Ife East	Ife East	Ife East
	Obokun	Ilesha West	Ifelodun	Ife South	Ife North	Ife North	Ife North
	Odo Otin	Irepodun	Ila	Ifelodun	Ife South	Ife South	Ife South
	Ola Oluwa	Irewole	Ilesha East	Ila	Ifedayo	Ifelodun	Ifedayo
	Osogbo	Isokan	Ilesha West	Ilesha East	Ifelodun	Ila	Ifelodun
		Iwo	Irepodun	Ilesha West	Ila	Ilesha East	Ila
		Obokun	Irewole	Irewole	Ilesha East	Irepodun	Ilesha East
		Odo Otin	Isokan	Isokan	Ilesha West	Irewole	Ilesha West
		Ola Oluwa	Iwo	Iwo	Irepodun	Iwo	Irepodun
		Olorunda	Obokun	Obokun	Irewole	Obokun	Irewole
		Oriade	Odo Otin	Odo Otin	Isokan	Odo Otin	Isokan
		Osogbo	Ola Oluwa	Ola Oluwa	Iwo	Ola Oluwa	Iwo
			Olorunda	Olorunda	Obokun	Olorunda	Obokun
			Oriade	Oriade	Odo Otin	Oriade	Odo Otin
			Osogbo	Osogbo	Ola Oluwa	Osogbo	Ola Oluwa
					Olorunda		Olorunda
					Oriade		Oriade
					Orolu		Orolu
					Osogbo		Osogbo

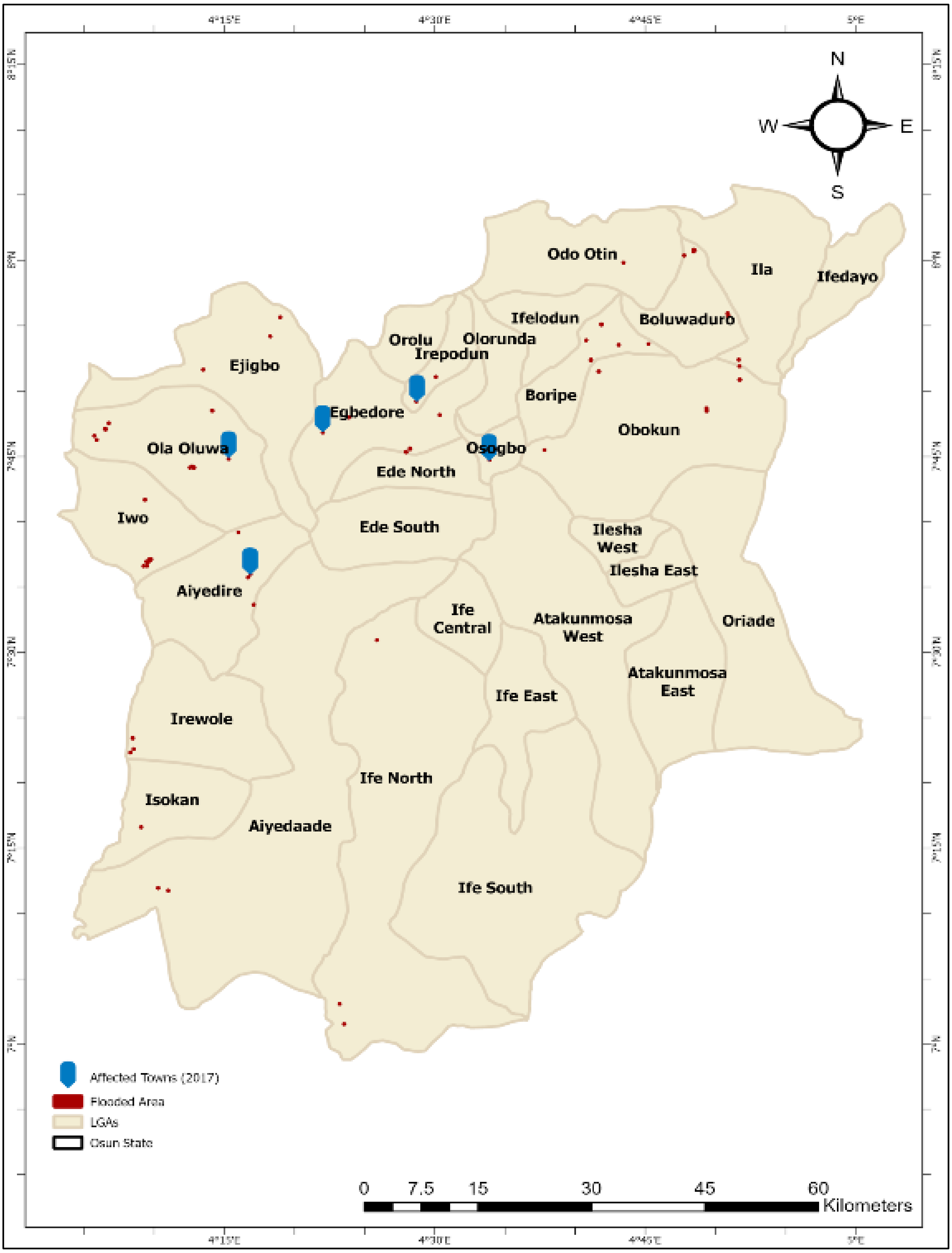

Figure 2 Map of Flood Risk Zones in 2017

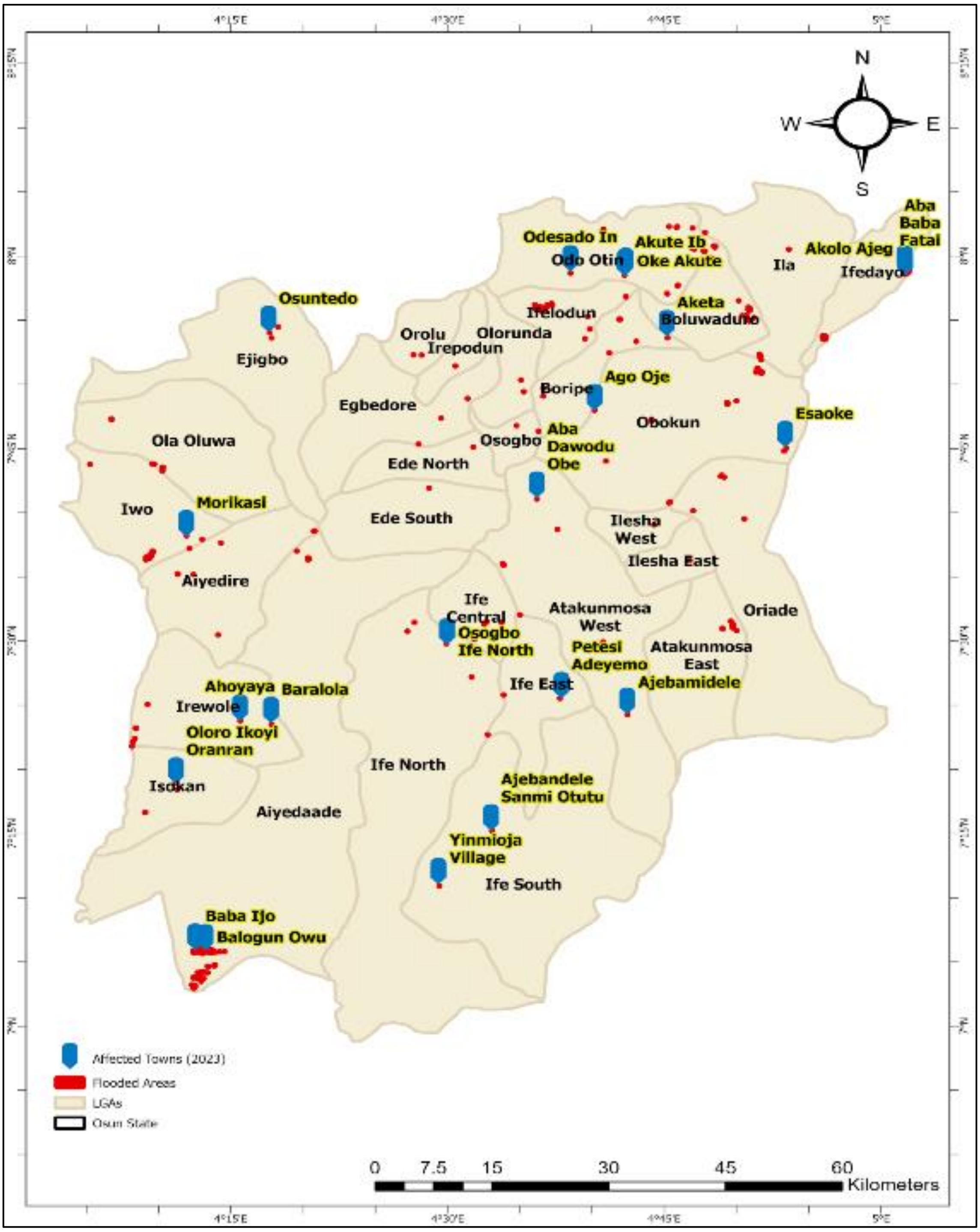

Figure 3 Flood Risk Zone of Osun State in 2023

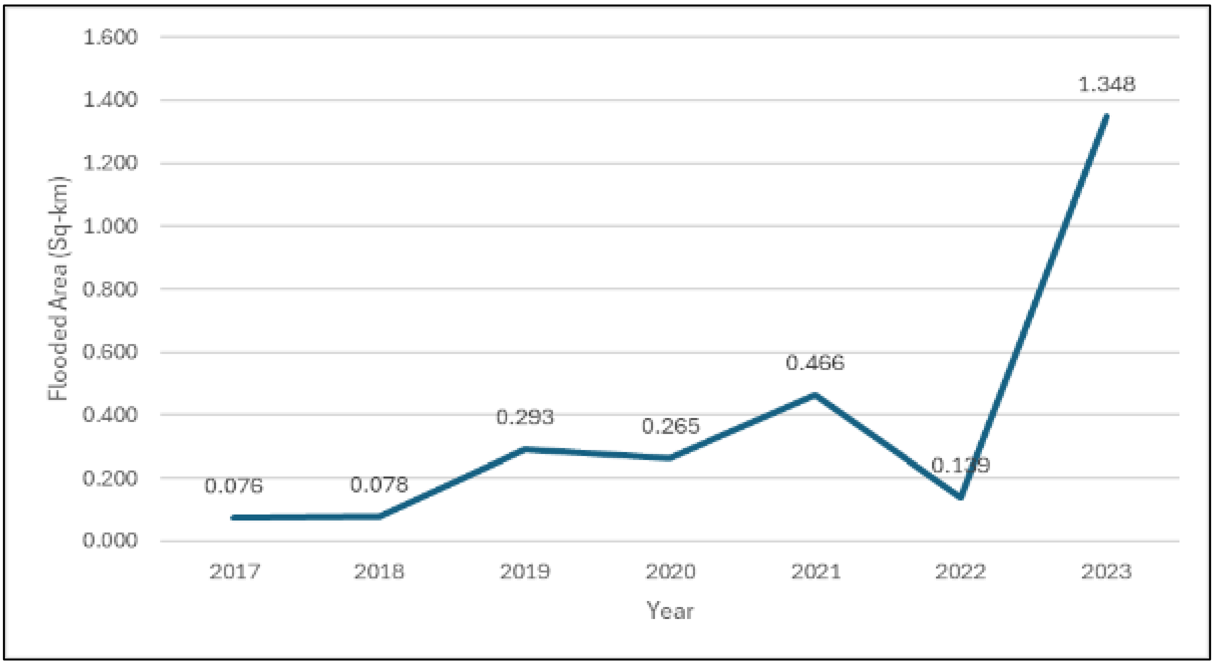

Figure 4 Flood Risk Zone Trend

Table 4 Flood Depth

Year	**LGA**	**Flood Depth (m)**			**Flood Depth Area (sq. m)**
		Min	Mean	Max	
2017	NA	NC	NC	NC	NC
2018	Irewole	1	1	1	956.419358
2019	Ila	1	1	1	956.419358
	Boluwaduro	3	5.75	8	3825.677433
	Ifedayo	1	1	1	956.419358
2020	Ife North	1	3.03	8	30605.41946
2021	Atakunmosa West	1	4	7	5738.516149
	Oriade	2	7.7	16	2869.258075
2022	NA	NC	NC	NC	NC
2023	Ifelodun	1	1.4	3	4782.096791
	Aiyedaade	1	1.84	7	67905.77443
	Ifedayo	1	2.4	9	62167.25828

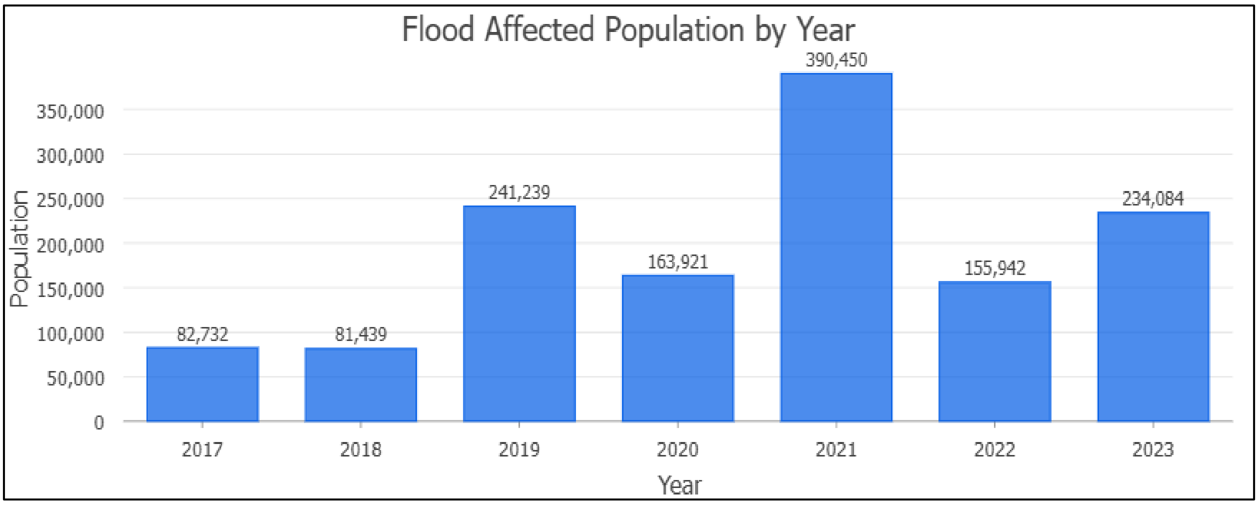

Figure 5 Flood Affected Population by Year

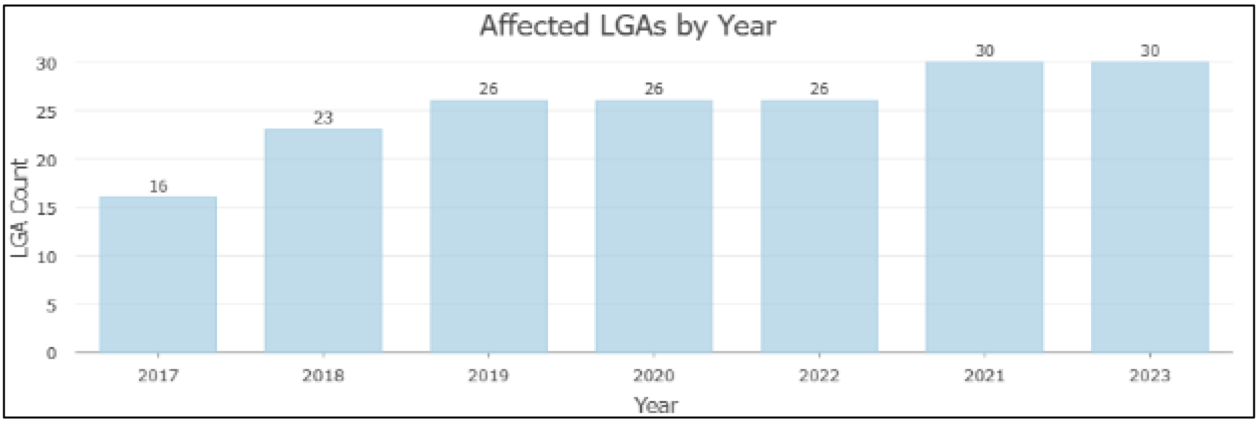

Figure 6 Affected Number LGAs by Year

4. Discussion of Findings

The findings of this study show that flooding in Osun State has shifted from a localized hazard to a widespread environmental crisis. Between 2017 and 2023, flood events expanded from affecting 16 Local Government Areas (LGAs) and just 0.076 km^2 of land to inundating all 30 LGAs, covering 1.348 km^2, an 870% rise within a single year, between 2022 and 2023. This reflects not only climate variability but also the increasing influence of human-induced pressures, such as land-use change and inadequate urban planning. While earlier floods were shallow (<1 m in 2018–2019), extreme depths exceeding 8–16 m were documented in Boluwaduro (2019) and Oriade (2021), underscoring the transition from nuisance flooding to catastrophic inundations. Such depth dynamics mirror broader patterns observed across Nigeria, including in the Niger Delta, where poorly drained soils amplify flood severity (Ologunorisa & Tersoo, 2006).

The spatial distribution of flood risk across Osun State highlights a significant geographical disparity between the central–western and eastern regions. Central and western LGAs such as Osogbo, Iwo, Egbedore, and Ola-Oluwa appear as consistent hotspots of vulnerability. This increased risk results from a combination of factors: the dominance of low-lying topography, which naturally encourages water accumulation; rapid and often unregulated urban growth, replacing permeable soils with impervious surfaces; and inadequate drainage infrastructure, which fails to properly channel excess stormwater during peak rainfall events. Collectively, these conditions lead to a cycle of inundation, infrastructure damage, and community displacement, increasing both the frequency and severity of flood impacts.

In contrast, LGAs located in the eastern highlands, particularly Oriade and Atakunmosa East, demonstrate a degree of resilience. Their higher elevations, rolling terrain, and dense vegetation cover provide protection by improving natural water absorption, decreasing surface runoff, and stabilizing soils against erosion. Vegetation, especially forested regions, functions as a natural buffer by slowing water flow and preserving the ecological health of the watershed. These biophysical benefits mean that, although the eastern highlands are not completely exempt from flood hazards, their risk level are significantly lower than that of the heavily urbanized western and central corridors.

5. Conclusions and Recommendations

This study concluded that between 2017 and 2023, central and western LGAs such as Osogbo, Ede North, Ede South, Ife Central, Iwo, Isokan, and Aiyedire emerged as flood recurrent hotspots due to low-lying terrain, urbanization, and poor drainage. Eastern LGAs such as Oriade, and Obokun were less affected due to higher elevation and vegetation cover. Moreover, annual flood-impacted LGAs increased with increasing time. Similarly, the flooded area increased from 2017 to 2023, exposing the weakness of current structural measures under extreme rainfall. The study thus recommended that the government should enforce floodplain zoning that can restrict high-density settlements in very vulnerable zones; adopt nature-based solutions which can protect wetlands and expand urban green spaces for natural water retention; and control land use expansion to implement urban containment policies to limit impervious surface growth.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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