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Machine learning-based flood extent mapping and damage assessment in Yenagoa, Bayelsa State, using Sentinel-1 and 2 imagery (2018-2022)

Becky P Bamiekumo[1*], **Emmanuella O Akpobome**[1], **Ayanka N Kemebaradikumo**[2], **Omabuwa O Mene-Ejegi**[3], **Desmond R Eteh**[1]

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Author Affiliation:
[1]Department of Geology, Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria
[2]Department of Geology, University of Port Harcourt, Rivers State, Nigeria
[3]Department of Environmental Management and Control, Rivers State University, Port-Harcourt, Rivers State, Nigeria

[*]Corresponding Author
Department of Geology, Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria
Email: bbpere07@gmail.com

Contact List

Becky P Bamiekumo	bbpere07@gmail.com
Emmanuella O Akpobome	akpobomeemanuella@gmail.com
Ayanka N Kemebaradikumo	ayankanelsondk@gmail.com
Omabuwa O Mene-Ejegi	Omabuwa.ejegi@outlook.com
Desmond R Eteh	desmondeteh@gmail.com

ORCID List

Becky P Bamiekumo	0009-0002-9941-4758
Emmanuella O Akpobome	0009-0007-1633-3554
Ayanka N Kemebaradikumo	0009-0003-8634-5383
Omabuwa O Mene-Ejegi	0009-0002-5262-3923
Desmond R Eteh	0000-0003-0660-6743

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ABSTRACT

The study utilizes the application of Sentinel-1 and Sentinel-2 satellite imagery between 2018 and 2022 in assessing flood extent and damages in Yenagoa, Bayelsa State, Nigeria, using machine learning techniques applied to Sentinel-1 and Sentinel-2 satellite imagery from 2018 to 2022. Synthetic Aperture Radar (SAR) data from Sentinel-1, with its all-weather capabilities, enabled the detection and mapping of the flood extent using machine learning algorithms, while Sentinel-2 multispectral images facilitated land-use classification before and after the flood events using support vector machines (SVM). The Shuttle Radar Topographic Mission (SRTM) and geological map were also used. This study, carried out using Google Earth Engine (GEE), Python, JavaScript, and ArcGIS 10.5, reveals a tremendous increase in the flood-affected areas, which expanded from 54.92 km² in 2018 to 90.15 km² in 2022. It found that the main drivers of such events were increased rainfall and rapid urbanization. The DEM data extracted from SRTM showed that the low-lying areas, specifically those with an elevation range of -6 m to 7 m (gentle slope, range from 1° to 9°), are the areas most prone to flooding. The geological composition, described as a swampy deltaic plain, contributed to prolonging the duration and severity of the flood. Machine learning analysis using Sentinel-2 imagery showed that vegetated and built-up classes are highly flooded, thus bringing socio-economic losses due to displacement of households and economic loss. This study has brought out the vital role of machine learning and remote sensing in flood detection and monitoring, besides the urgent need for data-driven flood risk management strategies integrating regional topography, land use dynamics, and geological factors.

Keywords: Flood extent, machine learning, GEE, Yenagoa, flood damage, Sentinel-1/2

1. INTRODUCTION

Flooding is one of the most frequent environmental disasters that seriously devastates human settlements and ecosystems worldwide, especially in low-lying areas like Yenagoa and Bayelsa State, Nigeria. The Yenagoa landscape falls within the Niger Delta area, characterized by a complex network of rivers, creeks, and swampy areas, making it highly susceptible to flooding during heavy rainfall and rainy seasons (Nwankwoala and Okujagu, 2021; Eteh et al., 2019; Eteh et al., 2024a). These frequent floods result in widespread displacement, destruction of infrastructure, and interruption of socio-economic activities and call for the urgent requirement of methodologies that could effectively monitor such floods and their damage assessments.

Geospatial technologies, in particular, have appeared as one of the vital options in the challenge at hand through Sentinel-1 and Sentinel-2 imagery that makes a detailed analysis of the extent of the flood and its attendant impacts possible (Eteh et al., 2024a). Flooding in Yenagoa is attributed to both natural factors and anthropogenic activities through aspects such as climate change, increased rainfall, sea-level rise, urbanization, deforestation, and oil exploration activities (Umar and Gray, 2022; Oladimeji and Ohwo, 2022). All these elements further increase the risk of flooding in the region through the destruction of drainage patterns that reduce the carrying capacity of the river channels. Besides, geological features like alluvial plains and poorly drained coastal swamps expose Yenagoa to this menace (Amukalli et al., 2018).

These combined challenges highlight the need to enhance flood mapping efficiency through advanced remote sensing, enabling evidence-based disaster managements. The different geospatial technologies are fast bringing in a sea change in flood management by providing essential data on the extent of flooding, water depth, and post-flood damages. Among these, Sentinel-1, a synthetic aperture radar (SAR) satellite, has proved very helpful for flood mapping and offers the advantage of all-weather and day-and-night imaging capabilities (Hitouri et al., 2024). Complementing this, Sentinel-2 optical imagery increases the depth in land cover classification and damage assessment, adding a deeper understanding of the consequences of flooding (Nhangumbe et al., 2023).

This way, the powers of both satellites are combined to give analysts the capability to study more precisely the dynamics of flooded areas. Within the period from 2018 to 2022, Yenagoa witnessed a series of serious flooding situations that destroyed several houses, farmlands, roads, and public infrastructure; disrupted socio-economic activities; and triggered several environmental issues, including soil erosion, water pollution, and biodiversity loss (Ajumobi et al., 2023; Echendu 2023). The combined use of Sentinel-1 and Sentinel-2 offers a full analysis of such flood events in detail, which helps find areas of high risk and formulate targeted disaster management strategies.

For example, Sentinel-1 radar data delineate areas inundated even under cloud cover, and high-resolution imagery using Sentinel-2 supports land-use or vegetation-cover change analyses that are important in wider contexts of the impacts of flooding (Corradino et al., 2019). The application of machine learning techniques has further expanded satellite image usage in the study of flood mapping and assessment of damage. For instance, it has been able to process Sentinel-1 data with CNNs to enable higher accuracy in the detection of floods by differentiating water from non-water pixels with high precision (Tavus et al., 2022). The use of Vision Transformers with differential attention metrics has also shown applicability in global flood detection, offering improved robustness across a wide range of environmental conditions (Saleh et al., 2023).

These ML improvements are quite helpful in places like Yenagoa, where field observation is usually limited by accessibility problems during flooding. Training ML algorithms on historically captured satellite data from 2018 to 2022 will be able to carve out flood patterns and, therefore, assist in near real-time monitoring and quick responses during actual flooding events (Dasgupta et al., 2024; Ighile et al., 2022). Thus, the combination of Sentinel-1 and Sentinel-2 imagery with ML methodologies forms an effective framework for flood extent mapping, which provides actionable insights to policymakers, urban planners, and disaster management agencies. The integration of geospatial technology and ML techniques in flood-prone areas has been made feasible in various studies.

For example, in Yenagoa, studies have applied GIS and remote sensing technologies for mapping flood-risk zones, thus providing critical data for urban planning and disaster mitigation efforts (Eteh et al., 2019; Olanipekun et al., 2024). In addition, the unprecedented flood disasters witnessed in Nigeria in 2022, whose level of damage surpassed that recorded during the horrific 2012 flood disaster, underpin the need to adopt innovative systems for monitoring flooding upon which recovery and mitigation initiatives should be predicated. Flooding in the Niger Delta area, of which Yenagoa is part, is more often a response of combined local rainfalls with the inflow of water from upstream (Eteh et al., 2024b). While satellite imagery has made the mapping of flood extents easier, it is also able to track changes in land use that influence the vulnerability to flooding. Research work shows that urbanization, deforestation, and expansion into infrastructure have changed the natural landscape of Yenagoa, limiting its absorbing potential and, therefore, increasing the risk of floods within this area.

Such monitoring through geospatial techniques becomes very important in gaining an understanding of flood dynamics while proposing interventions effectively (Oborie and Eteh, 2023; Etuonovbe, 2011). Therefore, the combination of Sentinel-1 and Sentinel-2 satellite imagery with machine learning methodologies offers a strong approach toward flood extent mapping and damage assessment in flood-prone regions like Yenagoa. The research paper will investigate the flood events within 2018-2022 and discuss the spatial and temporal change in flooding and their impacts on land use and human settlement. These findings are quite enlightening and support for evidence-based flood mitigation strategies that can be used to develop better disaster resilience and more sustainable urban planning.

Study area

Yenagoa is the capital of Bayelsa State and is situated in the Niger Delta area of the southern part of Nigeria, a geographical area made up of low-lying floodplains with a laboriously intertwined network of rivers, which include River Nun, Ekole River, Taylor Creek, and Epie Creek (Eteh et al., 2019). The area lies between latitude 4.9426° N and longitude 6.2714° E (Figure 1). Agriculture and fishing are the major activities that have predominantly characterized Yenagoa agriculture and fishing, their very vital communities for local livelihoods. The Niger Delta Region is known for large deposits of oil and gas reserves, coupled with serious environmental and social challenges. The road includes roads and footpaths that characterize the infrastructure in Yenagoa, thus providing easy access to various locations.

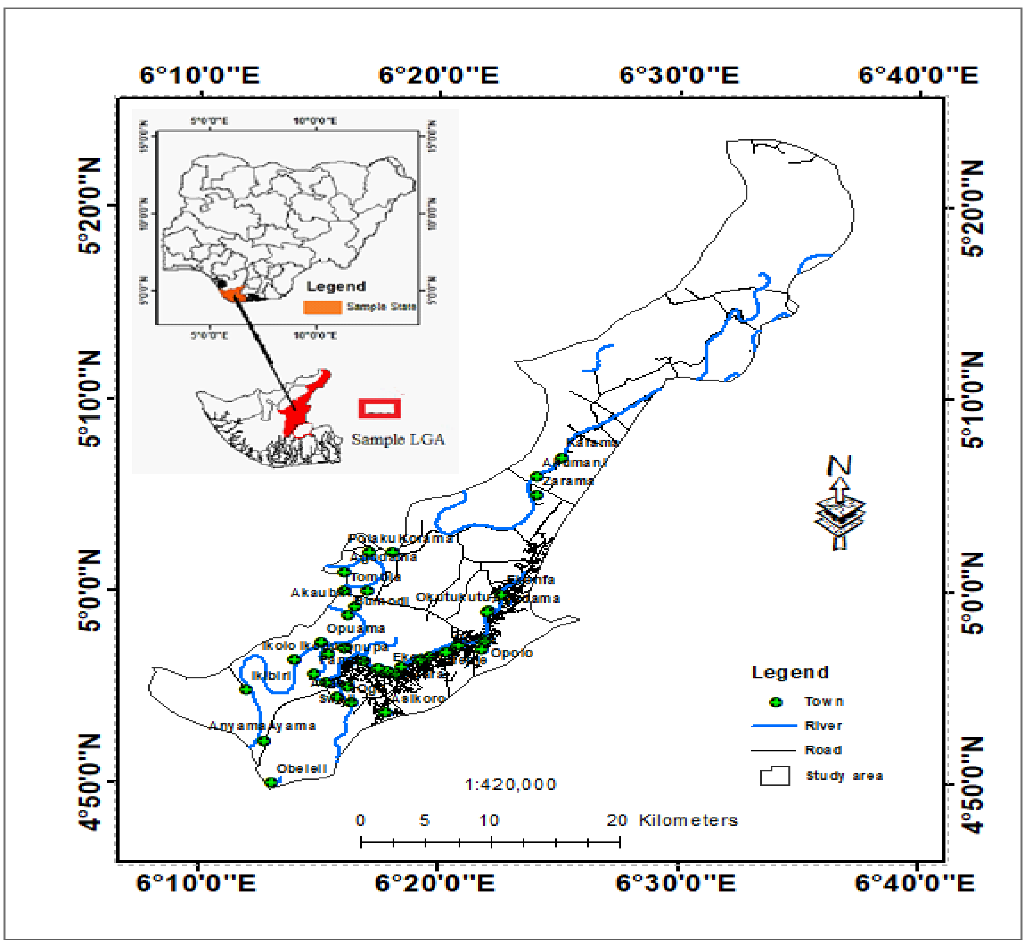

Figure 1 Study area map

The region hosts several hydrocarbon flow stations operated by the Shell Petroleum Development Company (SPDC) and Nigeria Agip Oil Company. The area receives high significant rainfall, with an estimated annual precipitation of about 4000 mm, making the Niger Delta a very vital area for groundwater recharge (United Nations Environment Programme, 2021). It has an almost two-seasonal climate season: Where the rainy season runs from late March to October, and the dry season runs from November to early March. Their brief respite, a short spell of cessation of heavy rains, occurs in mid-August.

Monthly temperature averages range from 25°C to 32°C, and hence the climate is a humid tropical environment. Vegetation regions are dictated by the varied soil types and organic matter accumulation in swamps, influencing vegetation patterns. They range from barrier island forests, mangrove forests, freshwater swamps, and lowland rainforests that support rich and dynamic swamp forest ecosystems to sustain large populations of the Niger Delta biodiversity Asuk et al., (2018); various plant species also contribute to the ecological complexity and productivity of its ecosystem.

2. METHODOLOGY

Materials

Data Collection

These multiscale datasets included satellite imagery, SRTM, and a Geologic map that were used during this work to give a comprehensive outline in relation to the hydrological and geological setting of the land-use patterns of the region under consideration. The main information sources are Sentinel-1 and Sentinel-2 imagery data, SRTM data, and geological maps.

Sentinel-1 SAR Imagery

Among several options of satellite missions, Sentinel-1 is a radar satellite mission that provides Synthetic Aperture Radar (SAR) data for flood mapping owing to its independence on weather conditions and suitability in frequently cloudy areas like Bayelsa State. The C-band imagery is selected for this imagery because the C-band can see the water on the surface. Data were acquired with the Sentinel-1 in IW swath mode, having a spatial resolution of 10 m, then further processed to GRD products. The data span the wet seasons of 2018-2022 for the detection of floods and delineation of water bodies. Data was acquired from the European Space Agency, https://scihub.copernicus.eu/, 2022.

Sentinel-2 MSI Imagery

High-resolution multispectral data from Sentinel-2 are very useful in classifying land use and LULC. The MSI mounted on Sentinel-2 delivers imagery of 13 spectral bands that are of immense use in the thorough study of vegetation, water bodies, and built-up classes. The Sentinel-2 data were used to find out the changes in land use before and after the floods. It gave insight into how many agricultural lands, forests, and urban zones were covered as a result of the flood. Data are acquired for the same period as Sentinel-1, providing additional multispectral information for the analysis. European Space Agency (ESA), 2022, https://scihub.copernicus.eu

Shuttle Radar Topography Mission (SRTM)

The SRTM DEM availed the topographic information required for the interpretation of water flow during the occurrence of flooding. Its 30-meter resolution elevation data allowed for identifying low-lying areas, slope assessment, and the modeling of hydrological patterns in Yenagoa. Acquired from the United States Geological Survey, this information has helped in the development of a hydrological model to assess the terrain that determines the extent of flooding (Eteh et al., 2024b).

Geological Maps

Geological maps of Yenagoa were used to understand the nature of the subsurface feature that is affecting the flood behavior. Information about the type of soils, rock formations, and the permeability of surface materials was integrated in interpreting how the terrain responds to flooding. These maps, from the Nigerian Geological Survey Agency, were important in correlating geological formations with flood-prone areas.

Method

Data Processing

Various platforms and tools are used to conduct preprocessing, information derivation, and analysis of satellite images in this study about flood mapping and assessment. The approach that would be followed in this study includes data pre-processing, spatial analyses, and advanced statistical modeling to ensure that the identification of flood extents and its impact analysis is accurate and comprehensive, as shown in (Figure 2).

Google Earth Engine - GEE

GEE was used as the main platform for the processing of both Sentinel-1 and Sentinel-2 satellite imagery because of its cloud computing capability and its vast dataset repository.

Pre- and post-processing of Sentinel-1 SAR data

Pre-processing steps, such as speckle noise reduction using the Lee filter, radiometric calibration for normalizing the pixel values, and terrain correction due to topographic distortions, have been carried out on Sentinel-1 SAR data. Cloud masking has been performed on Sentinel-2 multispectral data using the Sentinel-2 cloud probability dataset and further underwent atmospheric correction through the Sen2Cor processor (Gorelick et al., 2017; Zhu et al., 2020). These pre-processing steps help in acquiring accurate reflectance values, which are considered an essential source of information for land cover classification and flood analysis.

The flood extent was decided based on the range of values of the backscatter coefficient ($\sigma0$) in Sentinel-1 imagery. Areas with low values of ($\sigma0$) were considered as water bodies since SAR is sensitive to surface roughness and moisture content. These results were verified against NDWI, which was estimated using Sentinel-2 data:

$$\text{NDWI:}\frac{(\text{Green}-\text{NIR})}{(\text{Green}+\text{NIR})} \quad \text{Eq. 1}$$

Here, Green and NIR stand for Sentinel-2 special spectral bands. This thresholding in NDWI effectively served the segregation between water and no-water areas to complement flood delineation using SAR observations accordingly (Pham-Duc et al., 2017). Spatial analyses and cartographic visualization were performed in ArcGIS 10.5. Sentinel-1 and Sentinel-2 datasets, preprocessed in GEE, were imported into ArcGIS for further geospatial analysis, including geologic mapping and SRTM.

Flood Inundation Mapping

Flood inundation maps were created by overlaying SAR-derived flood extents with Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) data. Elevation differencing from SRTM DEM enabled the calculation of flood depths, providing a three-dimensional perspective on flood extent and severity.

$$\text{Flood Depth}=\text{DEMwater}-\text{DEMland} \quad \text{Eq. 2}$$

This method provided a spatial representation of flood severity across the study area.

Land Cover and Land Use Impact Analysis

The support vector machine was applied to classify the different categories of land cover, such as agriculture, urban areas, and forests, derived from Sentinel-2 imagery. In addition, the impact of the flood on each type of land cover was analyzed through the use of zonal statistics in ArcGIS. Buffer zones around main rivers and lakes were created to outline areas most susceptible to flooding. This will ensure that SAR, optical imagery, and DEM data integration guarantee a comprehensive assessment of flood impacts on both terrain and land use.

Python for Data Analysis

Python was used extensively for data analysis and automation of workflows. Temporal analysis of flood extent variations was enabled by libraries such as NumPy and Pandas in Python, allowing the organization and analysis of time-series data, thus enabling the said task. For instance, temporal changes in inundation extent were computed by comparing the pixel-based SAR-derived flood extents across different time intervals.

Machine Learning for Land Use Classification

The SVM was one of the algorithms executed on land cover classification using the Scikit-learn library in Python (Pedregosa et al., 2011). The accuracy of classification was determined by generating a confusion matrix. Generally, any custom workflows could be automated by integrating GEE with Python APIs. Scripts have been developed to efficiently extract flood extent and compare temporally affected areas.

Elevation and Slope Modeling

Python also supported terrain analysis by processing SRTM DEM data. Elevation and slope characteristics were modeled using the equation for slope (S):

$$\text{slope} = \arctan\left(\frac{\Delta z}{\Delta d}\right) \qquad \text{Eq. 3}$$

where Δz is the elevation change and Δd is the horizontal distance. These slope analyses informed hydrological modeling, particularly in identifying flow directions and accumulation zones.

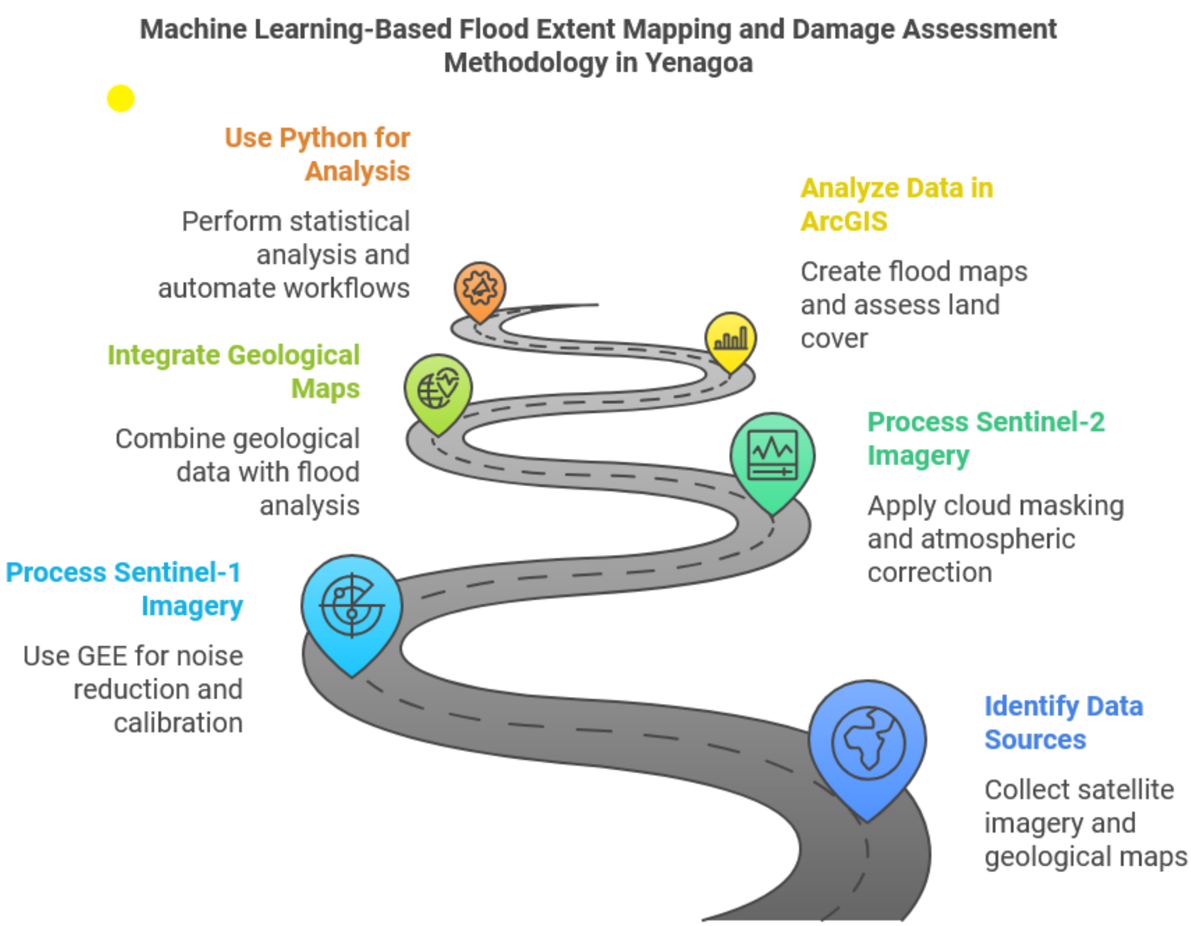

Figure 2 Flow chart diagram

3. RESULTS AND DISCUSSION

Flood Extent Analysis - 2018 and 2022

The flood area is highly increasing in Yenagoa, Bayelsa State. This was presented in Table 1 below, where the flood extent for 2018 increased significantly in 2022; hence, while the flood went from 54.92 to 90.15 km², non-flooding areas were reduced by about 35.23 km² in the study period. This marked increase in flooded areas can be attributed to several factors, including rising rainfall levels, alterations in land use patterns, and sediment deposition affecting river channels and floodplains.

Table 1 Flood and Non-Flood Extent in Yenagoa for 2018 and 2022.

Year	Flood Extent (km²)	Non-Flood Extent (km²)
2018	54.92	690.34
2022	90.15	655.11

Figures 3a and 3b show the spatial distribution of flooding for the comparative extent over both years. A wider reach was observed in 2022. This observed trend agrees with those in earlier studies, which pointed out that the increased spate of flooding in recent times within the Niger Delta region could be linked with increased precipitation due to climate change, coupled with extreme rain events (Eteh et al., 2024a).

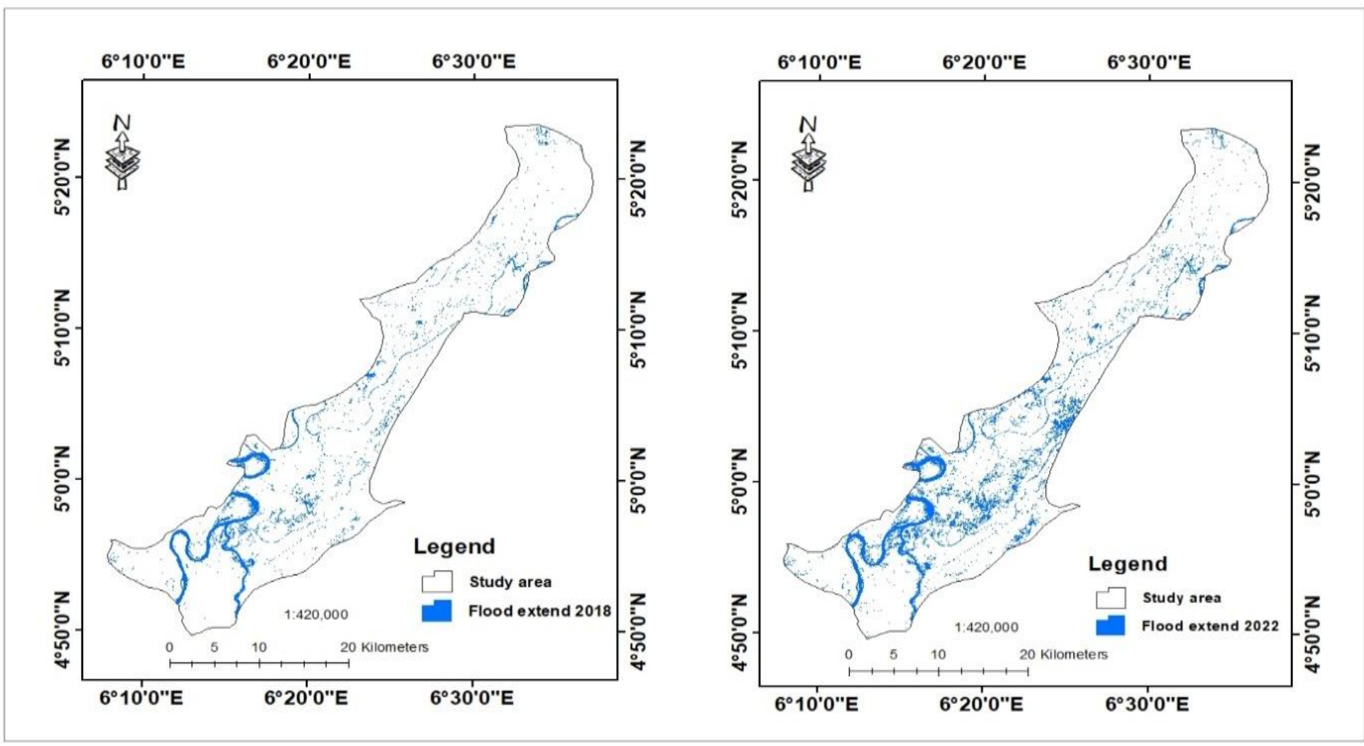

Figure 3a Flood extend in Yenagoa LGA, Bayelsa State, Nigeria for 2018 and 2022

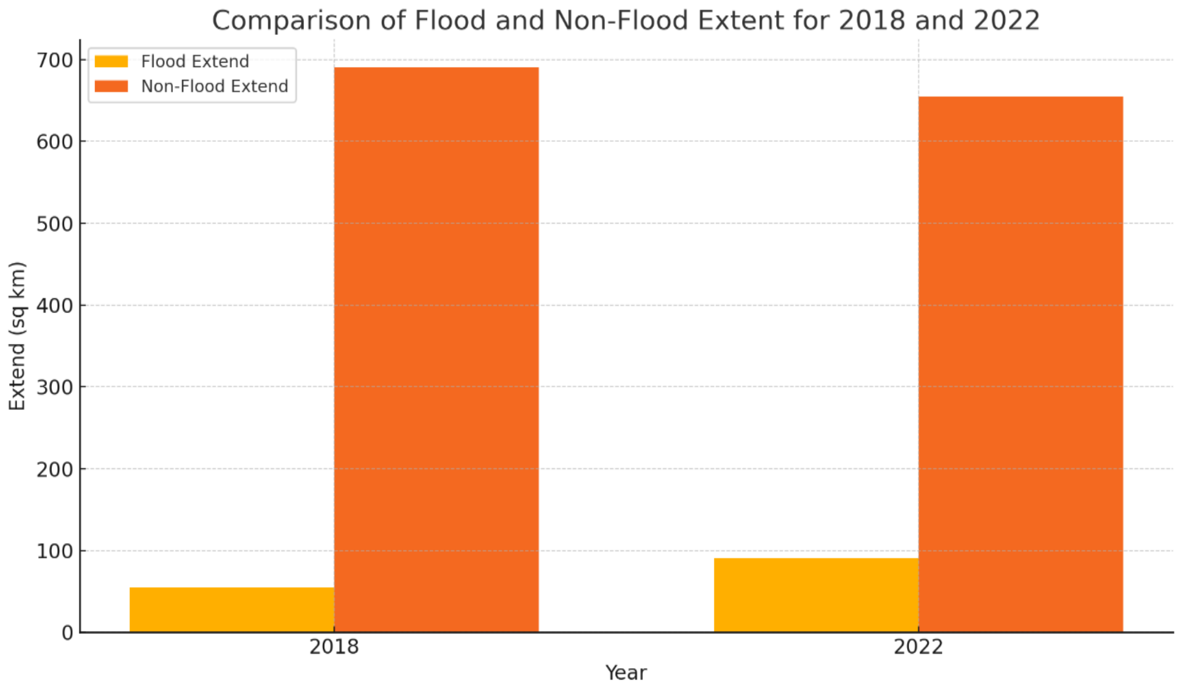

Figure 3b Flood and Non-Flood Extend in Yenagoa LGA, Bayelsa State, Nigeria for 2018 and 2022

Land Use Dynamics in Flood-Affected Areas for 2018 and 2022

The Sentinel-2 imagery was used for the land use analysis in both the flood and non-flood areas of Yenagoa, and the result is represented in Table 2 for the year 2018 and Table 3 for the year 2022. Land use classification before the flood and its change after the flood event highlighted the vulnerability of various classes of land use to flooding.

Table 2 Land Use for Flood-Affected and Non-Flood Affected Areas in 2018.

Classification	Before Flood (km²)	Flood Affected Area (km²)	Non-Flood Affected Area (km²)
Vegetation	634.73	21.6	613.13
River	27.86	24.72	3.14
Built-up Area	72.15	3.79	68.36
Bareland	10.52	4.81	5.71
Total	745.26	54.92	690.34

Highlights

Flood-affected areas in Yenagoa increased from 54.92 km² in 2018 to 90.15 km² in 2022, reflecting intensified flooding likely due to rising rainfall and land use changes.

Vegetation and built-up areas experienced higher flooding in 2022, highlighting the vulnerability of urban and natural landscapes to floods.

Lower elevation zones were more prone to flooding, with significant increases in flooded mid-elevation areas between 7.01 m and 22.00 m by 2022.

Table 3 Land Use for Flood-Affected and Non-Flood Affected Areas in 2022.

Classification	Before Flood (km²)	Flood Affected Area (km²)	Non-Flood Affected Area (km²)
Vegetation	590	35.3	554.7
River	28.59	26.15	2.44
Built-up Area	80.79	5.3	75.49
Bareland	45.21	23.4	21.81
Total	744.59	90.15	654.44

In 2018, it was 634.73 km², out of which 21.6 km² were submerged with water and 613.13 km² remained unflooded. In contrast, 35.3 km² more vegetative land was submerged during the flood in 2022, totaling 590 km² before flooding. Similarly, even built-up areas are facing an increased scenario of flooding; in 2018, it was 3.79 km², and in 2022, it is 5.3 km². The land use changes for the years 2001-2006 and the resultant affected zones are represented in Figures 4a to 4e, from which a clear increase can be identified to have taken place in the flooded areas covering built-up environments and vegetative regions.

Flooding into the built-up areas presents a severe implication on infrastructure and the livelihood of residents. A study by Ologunorisa, (2004) observed that flooding in urbanized zones is usually accompanied by large economic losses and displacement of people. This affirms the observation in Yenagoa, where expanded flooding in 2022 affected more built-up regions than it did in 2018.

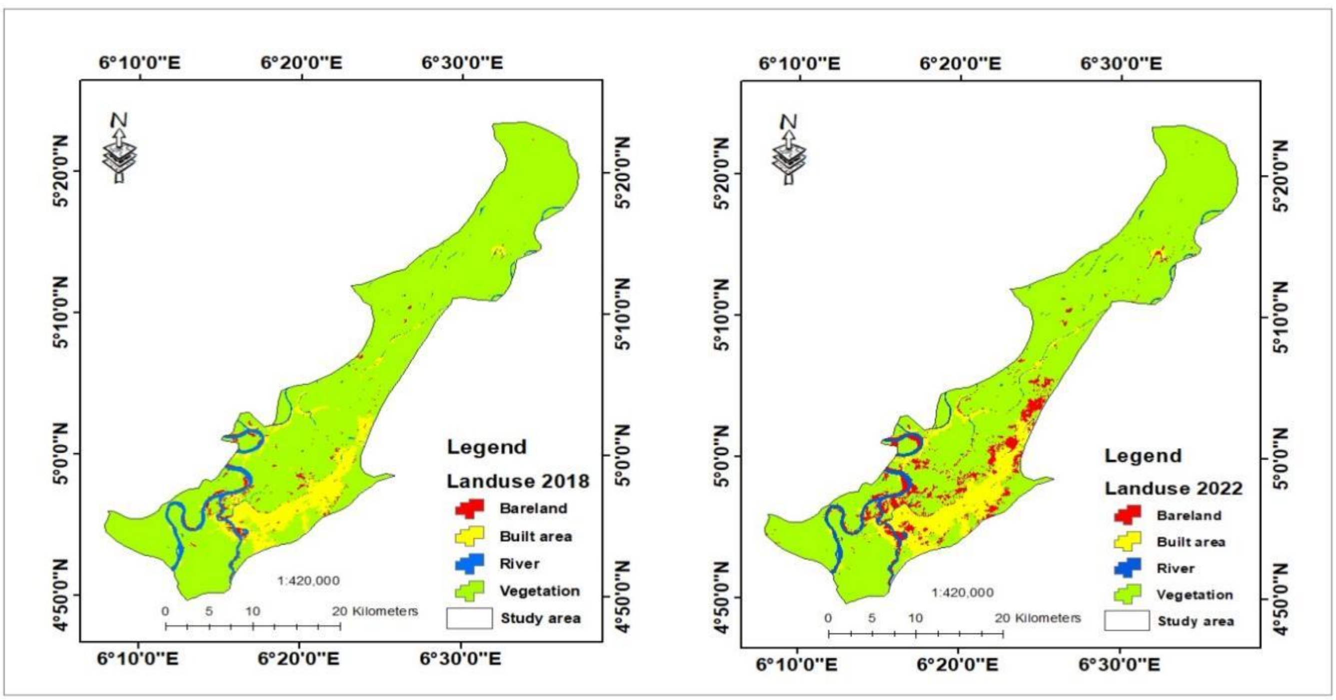

Figure 4a Landuse in Yenagoa LGA, Bayelsa State, Nigeria for 2018 and 2022

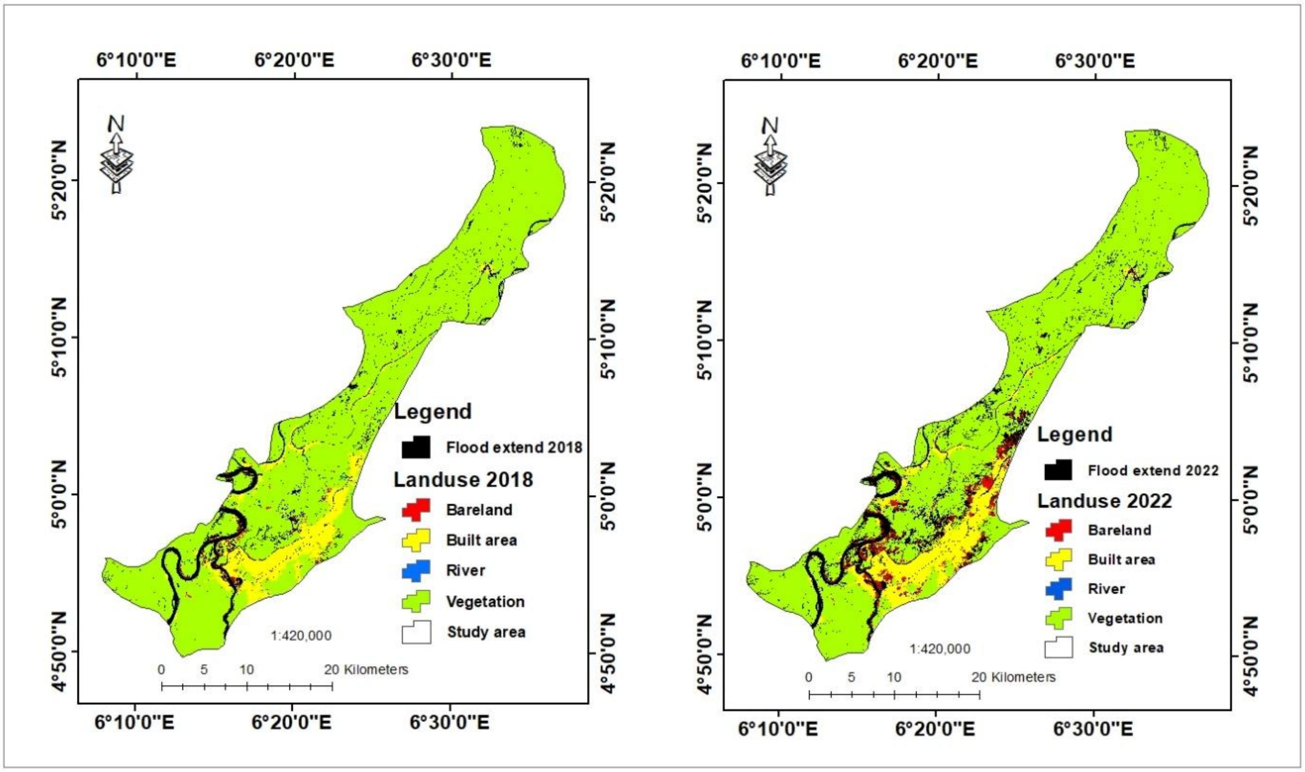

Figure 4b Flood Extend and landuse in Yenagoa LGA, Bayelsa State, Nigeria for 2018 and 2022

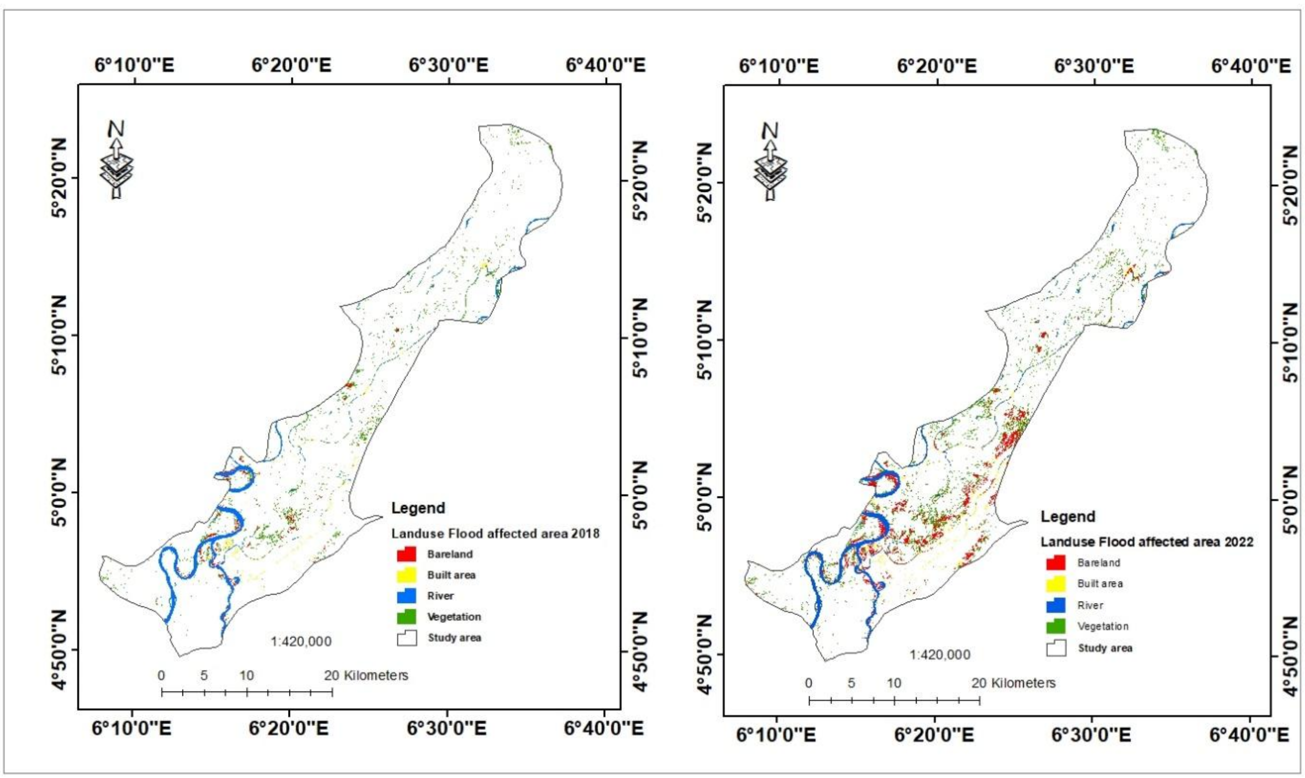

Figure 4c Landuse flood affected area in Yenagoa LGA, Bayelsa State, Nigeria for 2018 and 2022

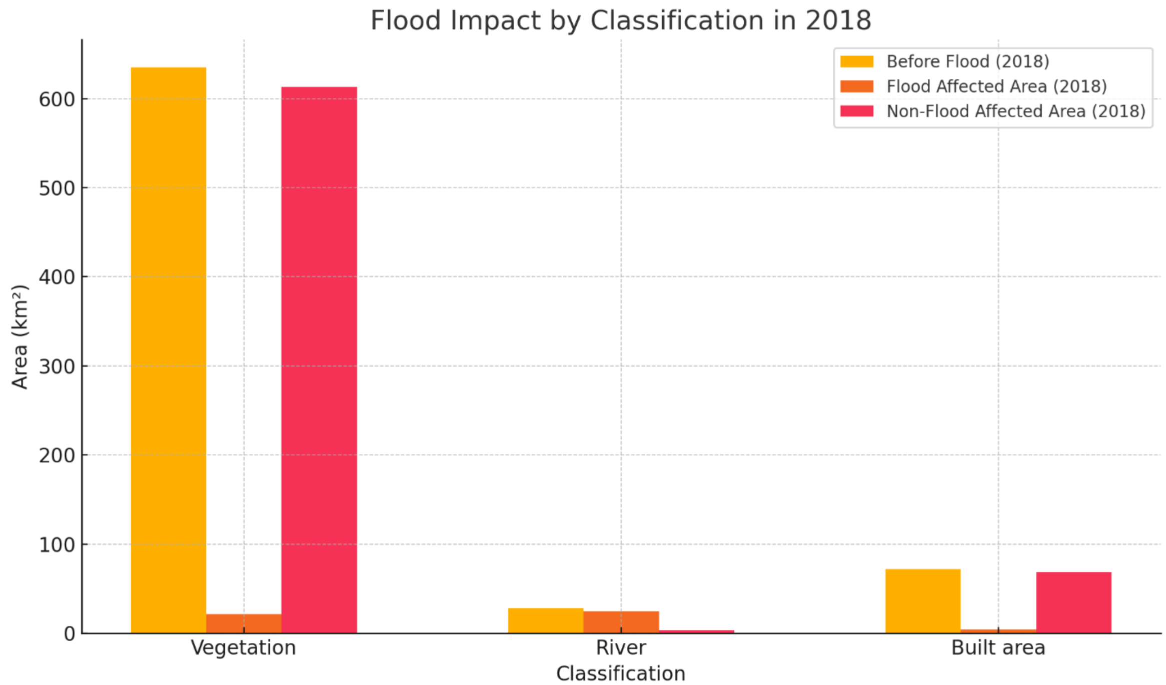

Figure 4d Land use for flood affected area and non-flood affected area for 2018 in Yenagoa LGA, Bayelsa State, Nigeria

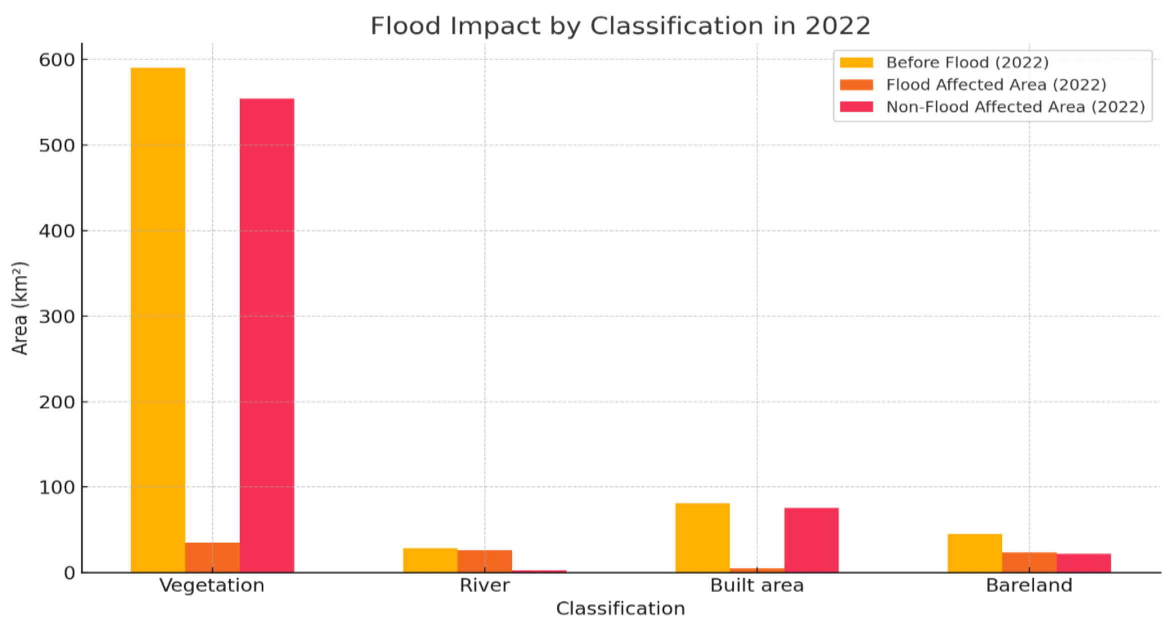

Figure 4e Land use for flood affected area and non-flood affected area for 2022 in Yenagoa LGA, Bayelsa State, Nigeria

Hydrological Patterns and Rainfall Data

The DEM represents the most determining factor in topographical features on flood extent. The lower-elevation areas, especially from -6 m to 7 m, according to the results of 2018 and 2022 (Table 4 and Table 5), are much more prone to flood-prone areas. In the same period, in 2018, the flood-affected area within this elevation range measured 16.81 km², which accounted for 30.61% of the total flooded area. This share has slightly increased in 2022, with 17.29 km² of the flooded area falling within this elevation range, meaning 19.18%. It can be observed that there is a significant rise in the flood extent of the mid-elevation zones, lying within 7.01 m and 22.00 m, from 2018 to 2022. Figure 5 also presents the DEM results with the elevation-based distribution of the flood, confirming that lower elevations are consistently more prone to flooding.

Table 4 DEM Analysis of Flood-Affected Areas in 2018.

Elevation (m)	Area (km²)	Percentage (%)
-6.00 - 7.00	16.81	30.61
7.01 - 13.00	11.29	20.57
13.01 - 18.01	11.43	20.82
18.01 - 22.00	10.77	19.61
22.01 - 38.00	4.60	8.38

Table 5 DEM Analysis of Flood-Affected Areas in 2022.

Elevation (m)	Area (km²)	Percentage (%)
-6.00 - 7.00	17.29	19.18
7.01 - 13.00	15.93	17.67
13.01 - 18.00	22.90	25.40
18.01 - 22.00	21.65	24.02
22.01 - 38.00	12.38	13.73

All these pieces of evidence of increased inundated areas in the mid-elevation zones, building up within an increase from 11.43 km² in year 2018 to 22.90 km² in year 2022 within an altitude range of between 13.01 to 22.00 m above mean sea level, show indications that higher rainfall could cause river water to overflow into the higher grounds. The findings are very consistent with the recent global findings on the striking influence of topography on the pattern of flooding. Low-lying areas, such as floodplains, are highly susceptible to flooding due to their proximity to bodies of water and low drainage capacity (Eteh et al., 2024b; Ekeu-Wei et al., 2020).

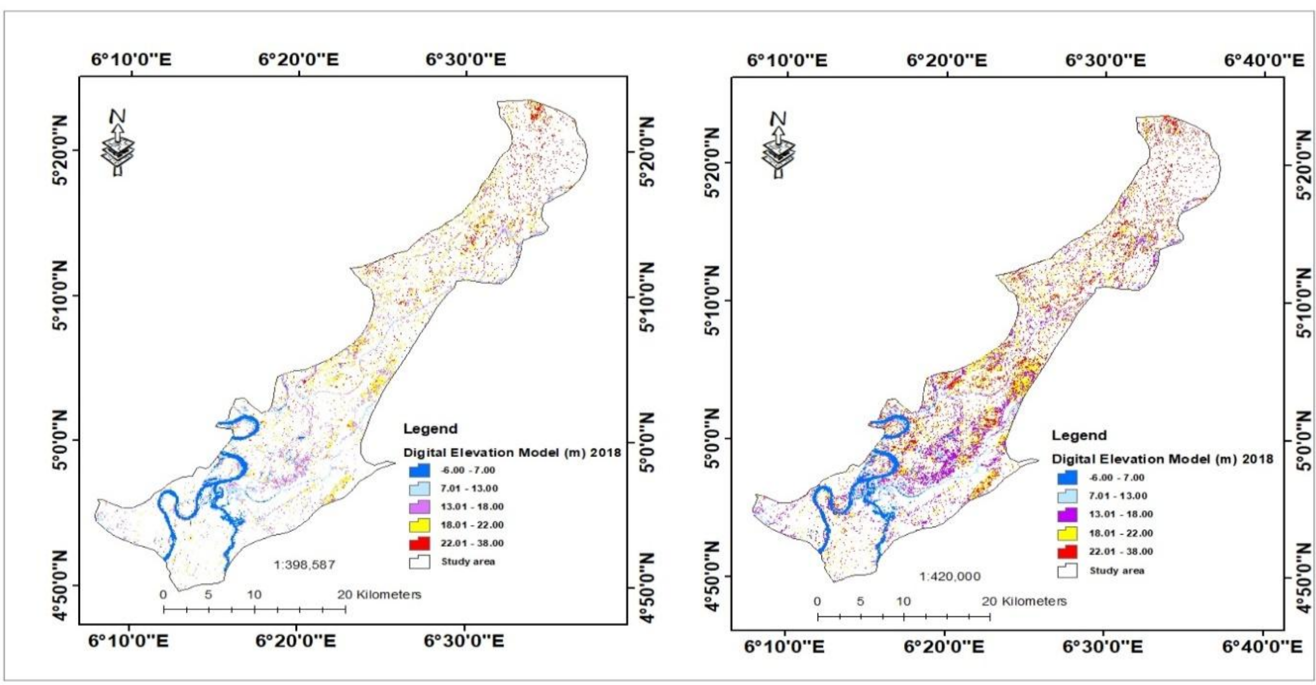

Figure 5 Digital elevation model flood-affected area in Yenagoa LGA, Bayelsa State, Nigeria, for 2018 and 2022

The slope of the terrain has also great importance in the determination of flood susceptibility; steep slopes are usually characterized by rapid runoff, hence reducing the time for the gathering of floodwaters. Slope analysis of the flood-affected areas was done for 2018 and 2022, represented in Tables 6 and 7, respectively. From this, it was observed that the gentle slope, ranging between 1° and 9°, was highly affected by flood conditions in both 2018 and 2022. Within this range of slope, 71% were flooded in 2018, while in 2022 this further increased to 75%.

Table 6 Slope Analysis for Flood-Affected Areas in 2018.

Slope (°)	Area (km²)	Percentage (%)
1°	16.17	29
1° - 9°	38.75	71

Table 7 Slope Analysis for Flood-Affected Areas in 2022.

Slope (°)	Area (km²)	Percentage (%)
1°	22.17	25
1° - 9°	67.98	75

This trend indicates that the relatively flat terrain of Yenagoa contributes significantly to its flood It thus follows from this trend that the generally flat topography of Yenagoa contributes a lot to its flood vulnerability. Figure 6: Spatial Slope-flood Extent Relationship. From the figure above, it is quite evident that flood effects on the gentle slope area are greater in both years, 2018 and 2022. The results are also consistent with the previous study in the region, Niger Delta, which showed a great relationship between slope and flood extents in very low-lying and flat land areas like Yenagoa (Etuonovbe, 2011). Its dominance by gentle slopes allows the accumulation of floodwaters, which prolongs the time of inundation, such as those of 2022.

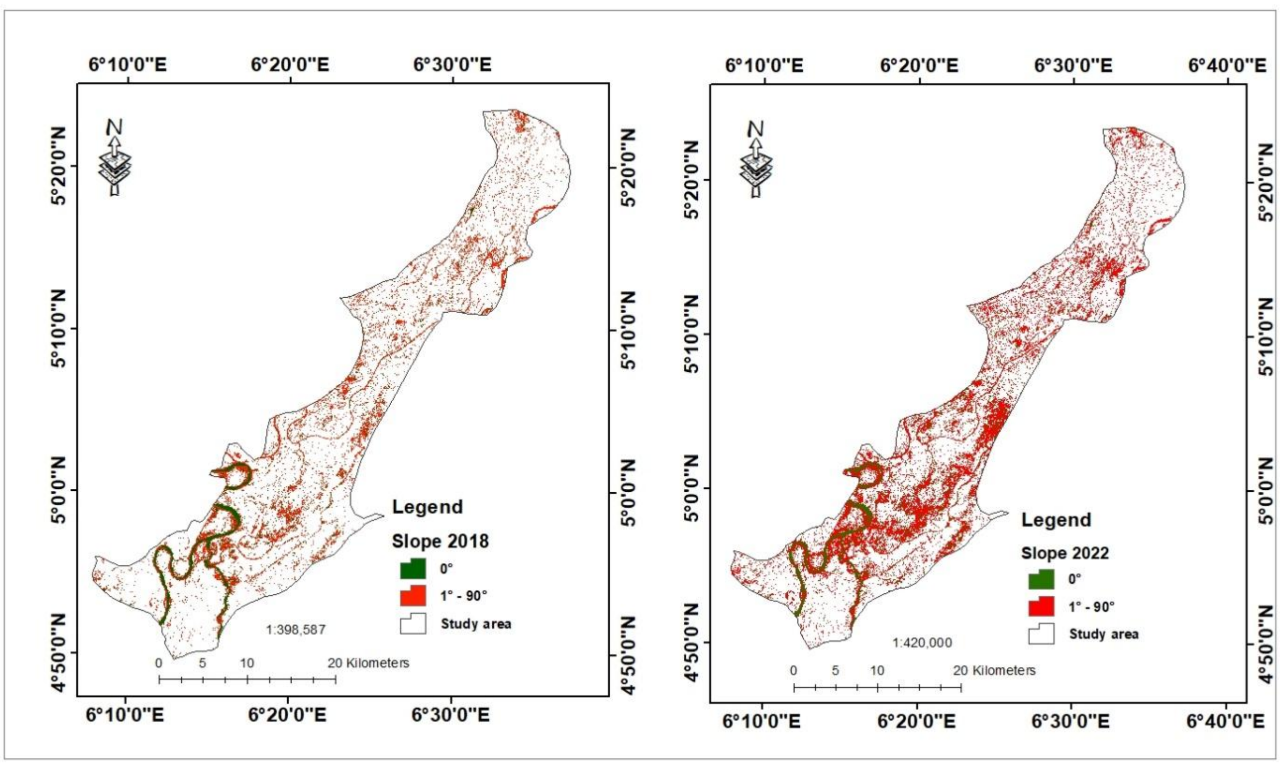

Figure 6 Slope flood-affected area in Yenagoa LGA, Bayelsa State, Nigeria, for 2018 and 2022

Geologically, Yenagoa is underlain mainly by meander belts, back swamps, freshwater swamps, and the Sombreiro deltaic plain, as observed in (Table 8 and Figure 7). These geological, especially swampy, areas have a high-water table and poor drainage capacity, which contributes highly to the susceptibility for flooding. The geological map (Figure 7) provides a visual representation of these formations, emphasizing the dominance of flood-prone swamps and low-lying areas within Yenagoa LGA

Table 8 Geological characteristics in study area

Geology	Area (km²)
Meander Belt, Back Swamps, Freshwater Swamps	743.1
Sombreiro Deltaic Plain	2.16

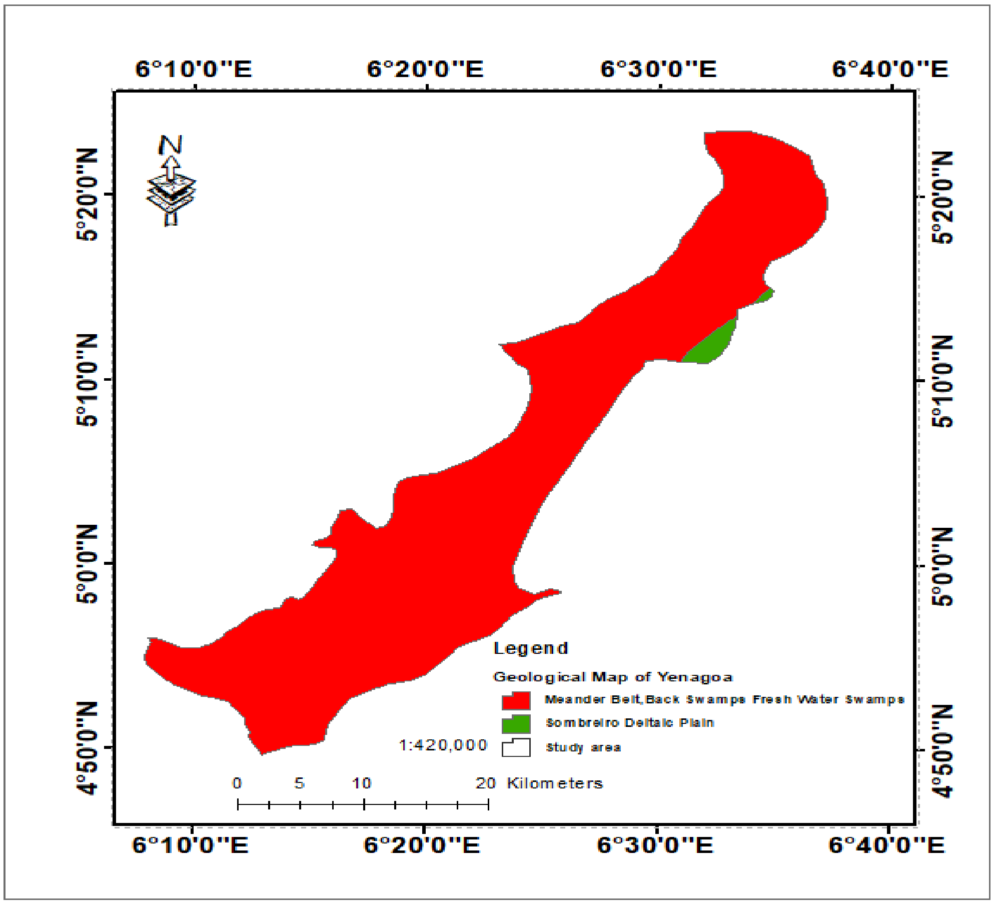

Figure 7 Geological map in Yenagoa LGA, Bayelsa State, Nigeria

This, therefore, presents the meander belt and swamp areas of 743.1 km², which, by nature, is susceptible to flooding, especially being a geological feature that is connected with hydrological linkages of the river systems. Also, swamps have land with low infiltration capacities of their soils; thus, a lot of surface water would always form with heavy rainstorm activity. Geologically, it serves to explain the 2018 and 2022 floods around Yenagoa. Excluding geological and topographic controls, recent rainfall intensity coupled with the hydrological patterns of the region contributes to the increasing trend of flood extension from 2018 through 2022.

Actual flooding around Yenagoa is greatly influenced by the overtopping of rivers resulting from cases of high-intensity and longer-duration rainfall. These incidences of increased rainfall also saw the area receive an above-normal quantum from an average of

2,500 mm in 2018 to above 3,000 mm as recorded by the Nigerian Meteorological Agency (NiMet) and local hydrological surveys within 2022, grossly contributing to higher levels in the rivers and further ensuring good surface runoff.

Table 9 Provides a summary of rainfall distribution for the study years, indicating a direct correlation between increased rainfall and flood extent.

Year	Average Rainfall (mm)	Peak Rainfall (mm)	Duration of Peak Rainfall (Days)
2018	2500	320	18
2022	3000	370	25

Larger rainfall and the duration of days with high rainfall explain more significant floods in the year 2022, which can be justified by using Table 9 and Figure 8, respectively. These results are in agreement with other studies done within similar regions that indeed, due to global climate change, the frequency and intensity of flooding in the Niger Delta will increase (Eteh and Okpobiri, 2021; Eteh et al., 2024a).

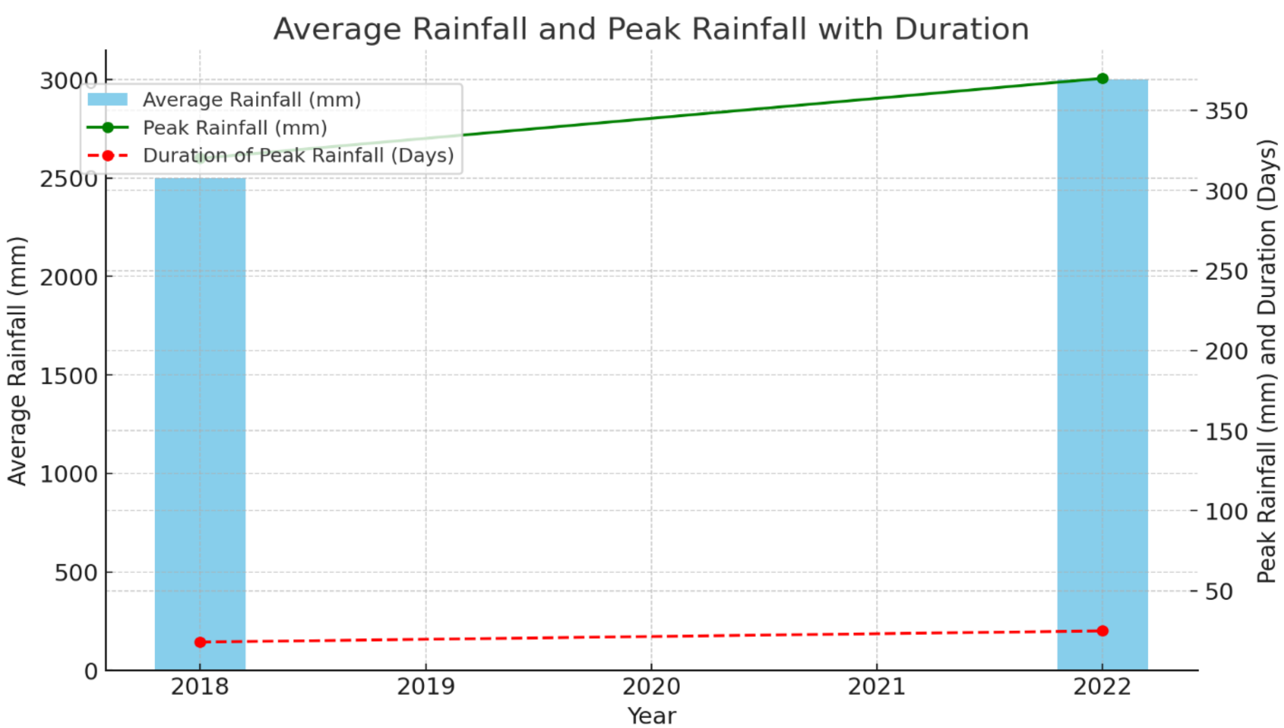

Figure 8 Rainfall patterns and their influence on flood extent in Yenagoa for 2018 and 2022.

4. CONCLUSION

This paper, therefore, undertakes a comprehensive flood extent analysis in Yenagoa, Bayelsa State, Nigeria, taking 2018 and 2022 as the years of focus. It thus infers that the flood areas increased from the flood extent in 2018 to 90.15 km² from 54.92 km². These factors may include an expansion that relates to a lot of rain increases, as well as some land use changes and perhaps sediments reaching the river channels to alter these floodplains.

Land use dynamics were analyzed using Sentinel-2 imagery, showing that areas of high vegetation and built-up areas were more flooded in 2022 compared to 2018. DEM results further revealed that the occurrence of flood events was easily noticeable within the low-elevation ground, though there is a remarkable increase in middle elevation that is flooded between 7.01 and 22.00 meters in the year 2022. Slope analysis shows that 1°-9° was higher for the two years and further suggests that generally flat topography contributes to flood vulnerability.

Limitations

Data Resolution: As the Sentinel-2 imagery used has a limited spatial resolution, the small-scale changes in land use and flood extents may easily be missed in the change detection analysis.

Climate Variability: The reliance of the study on only two years, 2018 and 2022, limits insights into longer-term flood trends and variability.

Model Assumptions: DEM and slope analyses are performed under conditions of a static state where changes in elevation or slopes due to sedimentation and erosion are not considered.

Geological Constraints: Though the study is of a geological nature, direct measurements of permeability and drainage capacity are not considered for better soil understanding.

Ethical Approval

Not applicable

Author Contributions

BPB, EDR and EO: A designed the study, wrote, and formatted the paper. Data processing was performed by EDR, ANK, BPB and OOM; EDR, EOA, OOM, ANK and BPB reviewed the work. All authors wrote and reviewed the final manuscript.

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Informed consent

Not applicable

Conflicts of interests

The authors declare that there are no conflicts of interests.

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Data and materials availability

Data that support the findings of this study are embedded within the manuscript

Satellite dataset: Sentinel-1 and 2 satellite data from the year 2018 to 2022 out of ESA were used due to their appropriateness for flood extent mapping. The considered data are openly available land products from the Copernicus Open Access Hubhttps://scihub,copernicus.eu/.

Topography Data: SRTM data were downloaded from USGS Earth Explorer: https://earthexplorer.usgs.gov/. 3. Geological map: from Nigerian Geological Survey Agency.

REFERENCES AND NOTES

1. Ajumobi VE, Womboh SB, Ezem SB. Impacts of the 2022 flooding on the residents of Yenagoa, Bayelsa State, Nigeria. GJEMPS 2023; 11(1):1-6.
2. Amukalli O, Bariweni PA, Imaitor-Uku EE. Partial distribution of heavy metals contaminants: indexes in soils around auto-mechanic workshop clusters in Yenagoa Metropolis, Bayelsa State, Nigeria. Glob J Earth Environ Sci 2018; 3(4):23-33. doi: 10.31248/GJEES2018.021
3. Asuk SA, Offiong EE, Ifebueme NM. Species composition and diversity of mangrove swamp forest in southern Nigeria. Int J Avian Wildlife Biol 2018; 3(2):159-164. doi: 10.15406/ijawb.2018.03.00078
4. Corradino C, Ganci G, Cappello A, Bilotta G, Hérault A, Del-Negro C. Mapping recent lava flows at Mount Etna using multispectral Sentinel-2 images and machine learning

techniques. Remote Sens 2019; 11(16):1916. doi: 10.3390/rs11161916

5. Dasgupta A, Sahu R, Hybbeneth L, Waske B. DeepFuse: towards frequent flood inundation monitoring using AI and EO. EGU Sphere 2024. doi: 10.5194/egusphere-egu24-20702
6. Echendu AJ. Human factors vs. climate change: experts' view of drivers of flooding in Nigeria. Nat Hazards Res 2023; 3(2): 240-246. doi: 10.1016/j.nhres.2023.04.002
7. Ekeu-Wei I, Blackburn G, Giovannettone J. Accounting for the effects of climate variability in regional flood frequency estimates in western Nigeria. J Water Resour Prot 2020; 12:690-713. doi: 10.4236/jwarp.2020.128042
8. Eteh DR, Egobueze FE, Francis O. Determination of flood hazard zones using geographical information systems and remote sensing techniques: a case study in part Yenagoa Metropolis. J Geogr Environ Earth Sci Int 2019; 21(1):1-9.
9. Eteh DR, Egobueze FE, Paaru M, Otutu A, Osondu I. The impact of dam management and rainfall patterns on flooding in the Niger Delta: using Sentinel-1 SAR data. Discov Water 2024a; 4:123. doi: 10.1007/s43832-024-00185-8
10. Eteh DR, Moses P, Egobueze FE, Okpobiri O. Utilizing machine learning and DSAS to analyze historical trends and forecast future shoreline changes along the River Niger. Res Sq 2024b.
11. Eteh DR, Okpobiri O. Floodplain mapping and risks assessment of the Orashi River using remote sensing and GIS in the Niger Delta region, Nigeria. J Geogr Res 2021; 4(2):10-16. doi: 10.30564/jgr.v4i2.3014
12. Etuonovbe AK. The devastating effect of flooding in Nigeria. Hydrogr Environ TS06J. 2011.
13. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens Environ 2017; 202:18-27. doi: 10.1016/j.rse.2017.06.031
14. Hitouri S, Mohajane M, Lahsaini M, Ajim-Ali Sk, Setargie TA, Tripathi G, D'Antonio P, Singh SK, Varasano A. Flood susceptibility mapping using SAR data and machine learning algorithms in a small watershed in northwestern Morocco Remote Sens 2024; 16(5):858. doi: 10.3390/rs16050858
15. Ighile EH, Shirakawa H, Tanikawa H. Application of GIS and machine learning to predict flood areas in Nigeria. Sustainability 2022; 14(9):5039. doi: 10.3390/su14095039
16. Nhangumbe M, Nascetti A, Ban Y. Multi-temporal Sentinel-1 SAR and Sentinel-2 MSI data for flood mapping and damage assessment in Mozambique. ISPRS Int J Geo-Inf 2023; 12(2):53. doi: 10.3390/ijgi12020053
17. Nwankwoala H, Okujagu DC. A review of wetlands and coastal resources of the Niger Delta: potentials, challenges, and prospects. Environ Ecosyst Sci 2021; 5:37-46. doi: 10.26480/ees.01.2021.37.46
18. Oborie E, Eteh DR. Flood influence using GIS and remote sensing-based morphometric parameters: a case study in Niger Delta region. J Asian Sci Res 2023; 13(1):1-15. doi: 10.55493/5003.v13i1.4719
19. Oladimeji OE, Ohwo O. Assessment of flood risk and mapping of flood risk zones in Yenagoa, Bayelsa State, Nigeria. J Appl Sci Environ Manage 2022; 26:219-226. doi: 10.4314/jasem.v26i2.7
20. Olanipekun OI, Nabage YA, Bala J. Flood risk assessment and its implications on critical infrastructure resilience in Nigeria. Afr J Environ Sci Renew Energy 2024; 17:69-85. doi: 10.62154/ajesre.2024.017.010471
21. Ologunorisa ET. Rainfall flood prediction in the Niger Delta, Nigeria. Int Conf Hydrol Sci Pract 21st Century, London, UK, 2004.
22. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J, Passos A, Cournapeau D, Brucher M, Perrot M, Duchesnay E. Scikit-learn: machine learning in Python. J Mach Learn Res 2011; 12(85):2825-2830.
23. Pham-Duc B, Prigent C, Aires F. Surface water monitoring within Cambodia and the Vietnamese Mekong Delta over a year, with Sentinel-1 SAR observations. Water 2017; 9(6):366. doi: 10.3390/w9060366
24. Saleh T, Weng X, Holail S, Hao C, Xia G. DAM-Net: global flood detection from SAR imagery using differential attention metric-based vision transformers. Elsevier 2023; 3-16. doi: 10.48550/arXiv.2306.00704
25. Tavus B, Can R, Kocaman S. A CNN-based flood mapping approach using Sentinel-1 data. ISPRS Ann Photogramm Remote Sens Spat Inf Sci 2022; V-3-2022:549-556. doi: 10.5194/isprs-annals-V-3-2022-549-2022.
26. Umar N, Gray A. Flooding in Nigeria: a review of its occurrence and impacts and approaches to modelling flood data. Int J Environ Stud 2022; 80(3):540-561. doi: 10.1080/00207233.2022.2081471
27. United Nations Environment Programme. Environmental assessment of Ogoniland. UNEP 2021.
28. Zhu Z, Wang S, Woodcock CE. Improvement and expansion of the Fmask algorithm: cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel-2 images. Remote Sens Environ 2020; 240:111697.