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# SAR-Based Flood and Waterlogging Extent Mapping Using Sentinel – 1 Time Series Backscatter Analysis: A Case Study of the FCT

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## ABSTRACT

Flooding is still one of the most important environmental dangers for rapidly urbanising communities, especially when the prompt flood monitoring is hindered by the continuous cloud cover and shortage of hydrological measurements. This study established a multi-temporal flood mapping methodology using Sentinel-1 Synthetic Aperture Radar (SAR) images and Google Earth Engine (GEE) to examine flood dynamics in the Federal Capital Territory (FCT), Nigeria, between 2019 and 2024. The workflow comprised the seasonal dry and wet season compositing, adaptive Otsu thresholding, permanent water masking and terrain filtering to yield annual flood maps, flood frequency products and persistent flood prone locations. Processing the Sentinel-1 SAR scenes produced six annual flood maps and corresponding flood statistics. The yearly flood extent varied between 39.98km$^2$ (2021) and 40.66km$^2$ (2022), with an average of 40.35km$^2$ and a total fluctuation of 0.69km$^2$ for the research period. Results showed that flooding continued to be spatially concentrated in key river corridors and floodplain ecosystems, demonstrating a strong temporal persistence of flood-prone locations. The adaptive thresholding method produced annual thresholds ranging from 2.87 to 3.37, and showed stable classification performance under various SAR backscatter conditions. The created procedure was effectively able to identify recurrent flood hotspots and provide a replicable cloud-based framework for operational flood monitoring. Our results show that the use of Sentinel-1 SAR imagery combined with Google Earth Engine offers an efficient and scalable approach for long-term flood assessment and supports evidence-based flood risk management, sustainable urban planning and climate adaptation in fast-growing metropolitan areas.

**Keywords:** Flood Mapping, Flood Frequency, Geospatial Analysis, Sentinel-1 SAR, Google Earth Engine, Synthetic Aperture Radar, Flood Risk, Urban Flooding

## INTRODUCTION

Flooding is a natural occurrence that cannot be entirely averted; it can lead to loss of life, destruction of property and infrastructure, and hinder economic progress. The preceding thirty years have constituted an extraordinarily inundation-laden era for Western Europe. The likelihood of heightened flood risk is expected to persist in the area as a result of climate change-related alterations in precipitation patterns (Cao *et al.*, 2023; Garg *et al.*, 2024). Instruments capable of detecting and precisely delineating regions susceptible to flooding are essential for the effective evaluation and management of this escalating flood threat. In this scenario, Earth Observation and Geographic Information System (GIS) methodologies present considerable benefits. Passive satellite imagery, including the USGS Landsat and ESA Copernicus Sentinel-2 initiatives, has been effectively employed to capture and identify floods at a catchment level (Chen *et al.*, 2022; Landuyt *et al.*, 2022). The historical image repository of Landsat has facilitated the examination of previous flood scenarios and supplied data to corroborate hydrological models (Tupas *et al.*, 2023). Nonetheless, a constraint of satellite systems that necessitate an unobstructed perspective of the Earth's surface is the problem of cloud cover. When cloud cover is significant, as frequently occurs during flooding, no valuable data can be gathered. Active technologies like synthetic aperture radar (SAR) are advantageous in this context due to their continuous operational capabilities and immunity to cloud interference. The application of SAR imagery for flood delineation is well-documented

(Matgen *et al.,* 2011; Mason *et al.,* 2012), and has gained significant traction following the launch of the ESA Copernicus Programme Sentinel-1 satellites (Martinis *et al.,* 2015; Cao *et al.,* 2019).

Conventional SAR-based flood mapping methodologies encompass histogram thresholding, active contour modelling, region growing, change detection, classification, and segmentation (Tupas *et al.*, 2024; Zhao *et al.*, 2024), whereas machine learning techniques are gaining prominence (Chen *et al.,* 2021; Tavus *et al.*, 2022). A prevalent method, histogram-based thresholding, categorises a bimodal histogram use a singular threshold value, beneath which pixels are designated as water. The establishment of the threshold is crucial, and various methodologies are available for its computation (Kittler and Illingworth, 1986; Li and Lee, 1993; Yen *et al.*, 1995). The thresholding procedure is fundamentally applied universally to the histogram of the whole swath of a SAR image. This method has limitations since it fails to consider the spatial context of picture pixels and is heavily reliant on the ratio of inundated regions within an image (Landuyt *et al.*, 2019). As a result, methods utilising split-based techniques have been created that employ representative regions of a picture with bimodal histograms for the purpose of thresholding (Zhuang *et al.,* 2024). This methodology facilitates the implementation of resilient automated thresholding with limited human intervention (Cao *et al.,* 2023). All thresholding methods are hindered by the inherent limitations of SAR concerning the identification of water amidst dense foliage. In vegetated regions, the backscatter signal and its capacity to infiltrate vegetation are influenced by various elements including biomass, forest classification, soil moisture, water depth, SAR wavelength, and polarisation (Dost´alov´a *et al.,* 2018; Tsyganskaya *et al.,* 2018).

L-band SAR is regarded as the most efficient and has been successfully utilised (le Toan *et al.,* 1997; Martinez and le Toan, 2007; Betbeder *et al.*, 2014), while the efficacy of shorter wavelengths, like the C-band employed by Sentinel-1, is reduced (Hess *et al.*, 2003). In Haile *et al.* (2023), framework, mitigation of adverse effects of vegetation on flood maps was posited by the utilisation of topographic data to autonomously adjust flood boundaries. The topographic adjustment of flood perimeters, in which the delineation of the identified water body was compared with a digital topographic model (DTM), which is more attainable due to the enhanced accessibility of high-precision DTMs. Techniques encompass the computation of pixel inundation levels at the land-water boundary (Hostache *et al.,* 2012; Mason *et al.,* 2012) or by dividing rivers into minor segments where water levels can be regarded as uniform (Matgen *et al.*, 2016; Zwenzner and Voigt, 2009). Subsequent advancements encompass the integration of computed water levels into hydrodynamic models (Giustarini *et al.*, 2011; García-Pintado *et al.*, 2015; Umar *et al.,* 2026) and the generation of flood depth maps (Matgen *et al.*, 2016; Brown *et al.,* 2016).

However, this study proposes a flexible, repeatable Google Earth Engine multi-temporal Sentinel-1 SAR process for flood mapping in the FCT with adaptive Otsu thresholding, terrain filtering, permanent water masking and flood frequency analysis (Garg *et al.*, 2023; Zhao *et al.*, 2024). Compared to previous studies mainly focusing on isolated flood events, the proposed framework detects persistent flood-prone environments in a 6-year (2019-2024) period, and provides a scalable approach for long-term flood monitoring and evidence-based urban flood risk management in data-constrained regions (Tupas *et al.,* 2023). The originality of this study is the construction of a multi-temporal Sentinel-1 SAR flood mapping framework in the Google Earth Engine environment for the Federal Capital Territory (FCT). The main difference to previous studies is that our approach integrates adaptive Otsu thresholding, terrain filtering, permanent water masking and flood frequency analysis to locate persistent flood-prone areas over a six-year period (2019-2024). Previous studies have mainly been limited to single flood events, and optical imagery (Cao *et al.,* 2023; Tupas *et al.*, 2024). This study provides a reproducible framework for long-term flood monitoring and evidence-based flood risk management. With urbanisation and flood dangers associated to climate change on the rise, the article highlights the growing need for fast and reliable flood monitoring. This study uses the latest Sentinel-1 SAR observations (2019-2024) and cloud-based Google Earth Engine processing to take advantage of modern geospatial technology to provide current flood information to aid sustainable urban planning, disaster risk reduction and climate adaptation in the FCT (Goffi *et al.,* 2020; Chen *et al.,* 2022). Consequently, the specific objectives of this study are;

1. To determine the extent of spatial and temporal flood and waterlogging in the FCT. using Sentinel-1 SAR time-series imagery.

2. To investigate the variance in Sentinel-1 backscatter characteristics between flooded and non-flooded surfaces during flood events.
3. To determine areas most susceptible to recurrent flooding and waterlogging within the FCT.
4. To provide the implications of the observed flood and waterlogging patterns for urban planning and flood risk management in the FCT.

### Significance of the Study

The study offers a significant contribution to disaster risk management, urban planning and environmental monitoring by establishing the applicability of Sentinel-1 Synthetic Aperture Radar (SAR) imagery for accurate mapping of floods and waterlogging irrespective of weather conditions. The result would help government agencies such as the Federal Capital Development Authority (FCDA), the Federal Capital Territory Administration (FCTA) and the National Emergency Management Agency (NEMA) in identifying flood prone areas and improving disaster preparedness, emergency response and land use planning. The study also contributes to sustainable urban development by providing spatial information that may be utilised to guide infrastructure design, drainage improvement and flood mitigation measures inside the increasingly urbanising areas of the Federal Capital Territory. Furthermore, the use of Google Earth Engine and free Sentinel-1 data offers a cost-effective and repeatable method for continuous flood monitoring in other Nigerian cities and other urban settings. This study contributes academically to the growing literature on SAR-based flood mapping in sub-Saharan Africa with practical evidence of application of Sentinel-1 time series backscatter analysis for mapping the flood and waterlogging dynamics. The developed methodological framework can be a reference for future studies on flood hazard assessment, climate resilience and geospatial disaster monitoring.

## METHODOLOGY

### Study Location

Figure 1 presents the study region which is Federal Capital Territory (FCT), Nigeria (8°25′-9°25′N and 6°45′-7°45′E) with an approximate land mass of 8,000 km2 (Saleh and Lay 2026). FCT is located in the natural setting of the Guinea Savannah. The FCT has six Area Councils, they are Abuja Municipal Area Council (AMAC), Bwari, Gwagwalada, Kuje, Abaji and Kwali. The location is the administrative capital of Nigeria and rapid urbanisation has caused major changes in land use, increased impervious surfaces and invasion of natural drainage systems, factors that contribute to the increasing flood risk (Shettima et al, 2026). FCT has a tropical wet and dry climate (Aw) with a clear wet and dry season. Apr-Oct Rainy season Nov-Mar Dry season Annual average rainfall is 1,100 to 1,600 mm with the highest showers in the period July to September. During rainy season the average temperature ranges from 22oC to 35oC and the relative humidity is high (Umar et al, 2026). This combination of climate variables, including a number of rain events that occur each year, resulting in excess surface runoff. This results in over burdening of natural and artificial drainage network especially in the fast-urbanising areas (FCDA, 2020). It's rolling plains, hills and valleys and enormous flood plains of the main rivers. The land is between around 300m and approximately 760m above sea level. The drainage system of the area is complex with major rivers such as Usuma, Gurara, Jabi and Wupa, minor seasonal streams and reservoirs that have a significant impact on the incidence of flood and retention of water in the area (Okonkwo, 2025). Flood plains are usually flat land next to a river. Flood plain systems and poorly drained depressions characterise them, The FCT vegetation type is a Southern Guinea Savannah with grasses, scattered shrubs and deciduous trees with riparian forest along the river corridors. Urban growth is connected with the reduction of natural plant cover and the increase of built-up area to reduce the infiltration capacity and increase the runoff generation in heavy rainfall events (Olusina and Okolie, 2018). The flood occurrence maps produced in this study indicate a comparable increase in flood frequency and longer duration of water logging in the south western (Kwali and part of Gwagwalada), central (AMAC and Kuje) and north western (Bwari) areas of the FCT. These are areas that are connected to large river systems and marshlands, reservoirs and low-lying areas where the run-off collects through natural processes (Abimbola et al, 2025). The FCT is prone to recurrent flooding due to the interaction of the weather conditions, geography, hydrological features, vegetation change and expanding urbanisation. “We need good flood risk management, sustainable urban development and better drainage infrastructure.

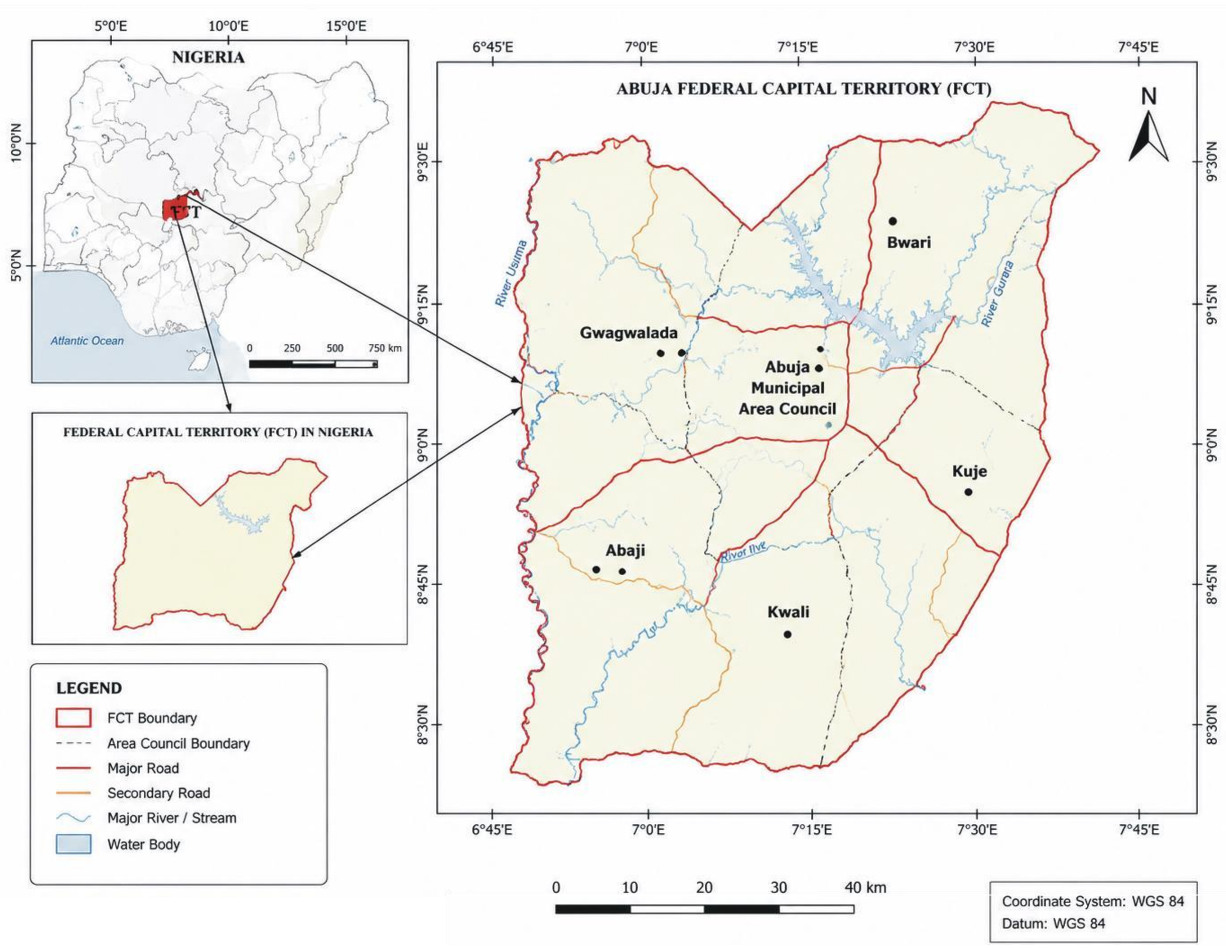


**Figure 1:** Map of the Study Area (FCT)

**Source:** ***Source:*** *GEE Output (2026).*

**Research Design**

The present study is a geographical remote sensing study with quantitative approach. The multi-temporal Sentinel-1 SAR pictures were processed in Google Earth Engine for identification and monitoring of the flood and waterlogging dynamics across time. The dataset is composed of Sentinel-1 SAR GRD images, Shuttle Radar Topography Mission (SRTM) DEM, Administrative boundaries of the FCT, Rainfall data and High-resolution photography. We acquired and selected Sentinel-1 images using Google Earth Engine (GEE). Criteria were acquisition date, orbit direction, polarisation (VV and VH) and time coverage. Pre-processing of SAR picture to Sentinel-1 photos before flood extraction involves orbit correction, thermal noise reduction, radiometric calibration, speckle filtering, terrain correction and trimming the image to the research region. These preprocessing approaches improve the image quality and offer dependable backscatter readings. The time-series SAR backscatter was analysed over several acquisition dates to look for temporal changes related to floods and waterlogging since the flooded surfaces often exhibit reduced radar backscatter due to specular reflection. Study of flood frequency and persistence multi-temporal flood maps were integrated to detect sites of frequent floods and prolonged waterlogging; The flood frequency was defined as the frequency of a pixel being classified as flooded throughout the period of observation. The reliability of the flood maps for accuracy assessment and validation is evaluated by using procedures comprising comparison with High-resolution satellite imagery, Reference datasets, Historical flood records and Visual interpretation. The geographical distribution of flood and waterlogging areas was estimated using GIS tools. This includes identifying flood hotspots, proximity to rivers and drainage canals and areas of recurrent inundation. Descriptive statistics, temporal comparison and geographical interpretation were applied to assess the collected flood maps and SAR backscatter information. Mapping, charting and summary data generation allowed the assessment of flood dynamics over the research period. The tools and platforms used in this study are Google Earth Engine, QGIS, SNAP and Python.

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### Methodological Workflow

Figure 2 shows the complete workflow summarising the research process from data acquisition to result generation. It illustrates the sequence of methodological steps.

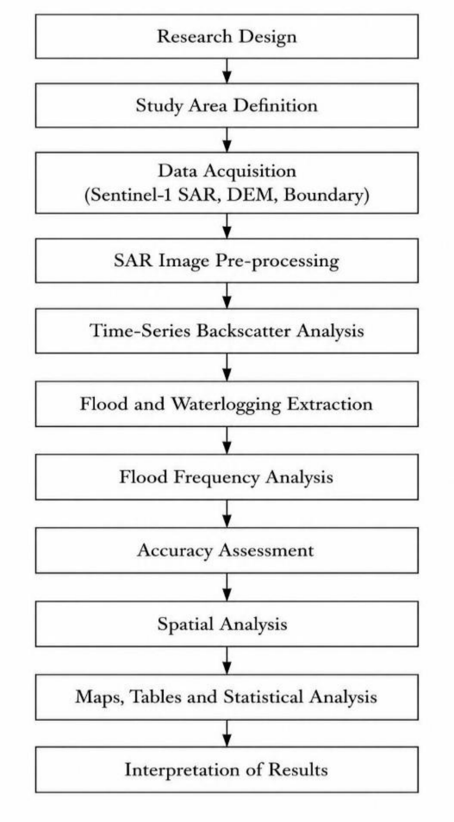


**Figure 2:** Methodological Flow

**Source:** Author’s Design

## RESULTS

### Annual Flood Area Statistics

Table 1 Flood Extent in the FCT (2019-2024) Using Sentinel-1 SAR Image The anticipated area of flooding remained rather steady during the research period, ranging from 39.98 km$^2$ in 2021 to 40.66 km$^2$ in 2022. The most floods mapped was in 2022, and the least was in 2021. Finally, there was no significant difference in annual extent of flooding overall showing that vulnerable locations were consistent across the years. The automatically determined Otsu criteria were between 2.87 to 3.37 which indicates that the classification was adjustable to inter-annual changes of the radar backscatter rather than a fixed threshold. This adaptive approach improves the robustness of flood detection by considering the interannual variation of meteorological variables and SAR signal quality. The extent of the re-occurring floods was rather uniform and confined to the known flood prone zones and there were no significant geographical variations throughout the time of study.

**Table 1:** Annual Flood Area and Otsu Threshold Values in the FCT (2019–2024)

| Year | Otsu Threshold | Flood Area (km$^2$) |
|---|---|---|
| 2019 | 3.1242 | 40.653 |
| 2020 | 2.8745 | 40.163 |
| 2021 | 2.8742 | 39.975 |
| 2022 | 3.3746 | 40.661 |
| 2023 | 3.1246 | 40.369 |
| 2024 | 3.1245 | 40.282 |

***Source:*** *GEE Analysis (2026).*

### Annual Flood Area Trend

Figure 3 shows the annual change in flood area for the FCT throughout the period of study. You can notice the year-to-year changes yet the general trend is quite stable. The flood area declined significantly from 40.65 km$^2$ in 2019 to 39.98 km$^2$ in 2021 and then climbed to 40.66 km$^2$ in 2022. Again, a small dip in 2023 and 2024. The absence of large variation is indicative of floods that occurred at recurrent areas across the six-year period. This tendency shows that local topography, drainage characteristics and existing flood plains may have more influence on flood dispersion than short term annual change. Flood mitigation and infrastructure design should therefore target these places that are recurrently inundated.

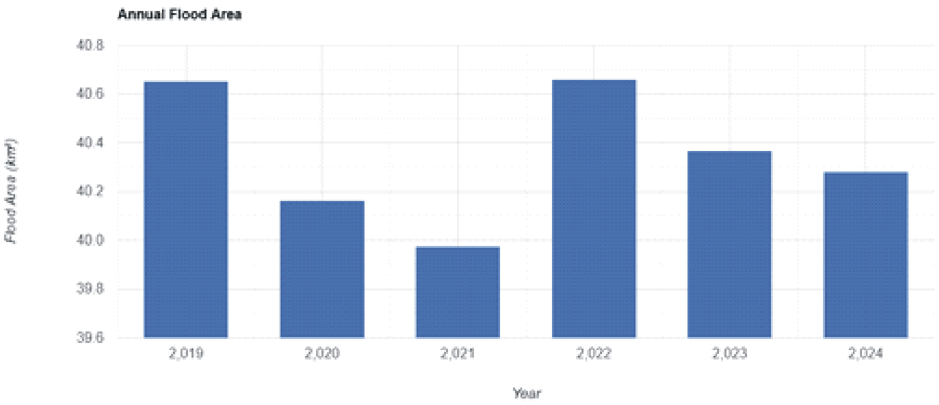


**Figure 3:** Annual Flood Area in FCT (2019–2024) ***Source:*** *GEE Analysis (2026).*

### Annual Flood Detection Thresholds

Table 2 Otsu thresholds developed automatically from Sentinel-1 SAR backscatter discrepancies for flood extraction in the FCT. The thresholds were between 2.87 and 3.37, indicating that the categorisation approach was updated to account for the interannual changes in the radar backscatter values, rather than using a fixed threshold for all years. The highest value was in 2022 (3.3746) while the lowest value was in 2020 (2.8745) and 2021 (2.8742). These discrepancies are due to changes in the statistical distribution of the radar backscatter and to seasonal surface moisture and flooding conditions. The Otsu technique removed the subjectivity of the flood classification and increased the consistency of the multi-temporal analysis by automatically determining the best threshold each year. The proposed adaptive thresholding approach improves the robustness of SAR-based flood mapping by adapting the classification for each year depending on the general image features instead of a fixed, arbitrarily determined threshold.

**Table 2** Annual Otsu Thresholds Used for Flood Classification (2019–2024)

| Year | Otsu Threshold |
|---|---|
| 2019 | 3.1242 |
| 2020 | 2.8745 |
| 2021 | 2.8742 |
| 2022 | 3.3746 |
| 2023 | 3.1246 |
| 2024 | 3.1245 |

***Source:*** *GEE Analysis (2026).*

### Annual Flood Classification Summary

The results of the annual flood mapping workflow are summarised in Table 3. Flood maps, adaptive Otsu thresholds and flood area estimates were successfully produced for each year from 2019 to 2024, indicating that the workflow processed all annual Sentinel-1 picture composites consistently. The successful production of these outputs demonstrated that the implemented processing sequence of seasonal compositing, SAR backscatter change detection, adaptive thresholding, permanent water masking and terrain filtering was able to delineate annual flood extents over the study period. The consistency of the output all through the six years gives trust in the robustness and repeatability of the workflow making it appropriate for long-term flood monitoring and temporal comparisons inside the FCT. Moreover, the annual threshold values and flood area statistics can provide a quantitative basis for interannual flood dynamics assessment and help subsequent spatial assessments of flood frequency and persistent inundation patterns.

**Table 3:** Summary of Annual Flood Classification Results (2019–2024)

| Year | Flood Map Generated | Threshold Determined | Flood Area Calculated |
|---|---|---|---|
| 2019 | Yes | Yes | Yes |
| 2020 | Yes | Yes | Yes |
| 2021 | Yes | Yes | Yes |
| 2022 | Yes | Yes | Yes |
| 2023 | Yes | Yes | Yes |
| 2024 | Yes | Yes | Yes |

***Source:*** *GEE Analysis (2026).*

**Summary Statistics of Annual Flood Extent (2019–2024)**

Table 4 shows the descriptive statistics of expected yearly inundation for the FCT (2019-2024) The study found an average annual flooded area of roughly 40.35km$^2$, the largest annual flooded area of 40.66km$^2$, and the smallest annual flooded area of 39.98km$^2$. The number found (0.69 km$^2$) indicates that the yearly flood extent remained rather consistent during the duration of inquiry. The figures illustrate that the flooding was limited to repeated places without a large increase or decrease in spatial area, although there were moderate fluctuations from year to year. The consistency indicates that occurrence of floods in the FCT is governed by permanent environmental restrictions such as topography, drainage networks and existing floodplains. Measures to cope with flooding should therefore be targeted at such regularly impacted areas with better drainage infrastructure, land use limitations and early warning systems. Descriptive statistics further show the robustness of the present SAR-based approach in generating similar flood forecasts over numerous years.

**Table 4:** Descriptive Statistics of Annual Flood Area

| Statistic | Value |
|---|---|
| Number of Years | 6 |
| Maximum Flood Area (km$^2$) | 40.661 |
| Minimum Flood Area (km$^2$) | 39.975 |
| Range (km$^2$) | 0.686 |
| Mean Flood Area (km$^2$) | 40.351 |

***Source:*** *GEE Analysis (2026).*

**Performance of the SAR-Based Flood Mapping Workflow**

The outputs generated from the designed SAR-based flood mapping procedure are summarised in Table 5. A total of 349 Sentinel-1 SAR scenes were processed to generate annual dry and wet season composites for the period 2019–2024. The workflow was able to provide six change detection images and six flood maps with flood statistics for each year, indicating that the processing chain performed robustly during the whole study period. In addition to annual flood maps, the workflow generated flood frequency and persistent water logging layers, which allowed for the study of flood behaviour in both temporal and spatial terms. These findings demonstrate the capability of Google Earth Engine in processing multi-temporal SAR datasets efficiently for a regional flood assessment. The effective implementation of each processing step also demonstrates that the established workflow can be applied for comparable flood monitoring studies in other places where there is a lack of cloud-free optical imagery and the radar data give a more robust basis for flood identification.

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**Table 5:** Summary of Processing Outputs

| Processing Stage | Output |
|---|---|
| Sentinel-1 Images Processed | 349 |
| Study Period | 2019–2024 |
| Annual Composites Generated | 6 |
| Change Detection Maps | 6 |
| Flood Maps Generated | 6 |
| Flood Statistics Generated | Yes |
| Processing Stage | Output |
| Flood Frequency Map | Generated |
| Persistent Waterlogging Map | Generated |
| Annual Flood Chart | Generated |

***Source:*** *GEE Analysis (2026).*

**Temporal Assessment of Flood Extent in the FCT (2019–2024)**

Table 6 displays Year on Year Change in the FCT Flood Extent, 2019-2024 The flood area reduced by ~0.49km$^2$ from 2019 to 2020 and more in 2021. The highest increase was in 2022 with a forecasted flooded land area of ~0.69 km$^2$ or 1.72% higher than the previous year. In 2023 and 2024 the water extent dropped again only slightly. Most annual percentage variations were <2%, indicative of rather moderate interannual variability in flood extent. Thus, flooding in the FCT was marked by frequent inundation of identified flood prone places rather than broad inundation of new regions. The pattern of damage over time indicates that flood prevention efforts must focus on these repeatedly affected areas, but also take into account the year-to-year climate variability that might affect the intensity of the flood.

**Table 6:** Annual Change in Flood Extent

| Year | Flood Area (km$^2$) | Change from Previous Year (km$^2$) | Percentage Change (%) |
|---|---|---|---|
| 2019 | 40.653 | – | – |
| 2020 | 40.163 | -0.490 | -1.21 |
| 2021 | 39.975 | -0.188 | -0.47 |
| 2022 | 40.661 | +0.686 | +1.72 |
| 2023 | 40.369 | -0.292 | -0.72 |
| 2024 | 40.282 | -0.086 | -0.21 |

***Source:*** *GEE Analysis (2026).*

**Summary of Multi-Temporal Flood Behaviour**

Table 7 provides a summary of the general temporal nature of flooding in the FCT over the period of investigation. The research suggests that the flood occurrence was reasonably consistent during the 6 years with small variations in the yearly flood extent. The 2022 flood extent was the greatest, but the difference from the smallest extent in 2021 was minimal, suggesting that flooding was still limited to known flood-prone regions. The observed yearly regularity is indicative of the role of landscape attributes such as topography, drainage arrangement and floodplain morphology in the occurrence of floods. The flood risk management techniques in these flood prone locations should thus be orientated towards long term measures rather than short term emergency solutions only. The multi-temporal assessment also shows the utility of Sentinel-1 SAR imaging to track yearly flood dynamics under changing environmental conditions, with a consistent detection capability throughout the study period.

**Table 7:** Characteristics of Flood Behaviour during the Study Period

| Indicator | Observation |
|---|---|
| Observation period | 2019–2024 |
| Number of annual flood maps | 6 |
| Indicator | Observation |
| Overall flood pattern | Relatively stable |
| Highest flood extent | 2022 |
| Lowest flood extent | 2021 |
| Largest annual increase | 2021–2022 |
| Overall temporal trend | Minor annual fluctuations |

***Source:*** *GEE Analysis (2026).*

**Annual flood extents across the FCT**

Figure 4 shows the spatial distribution of annual flood extents over the FCT for the period 2019-2024. The six-panel comparison reveals that floods during the research period were predominantly concentrated along major river courses, floodplains, reservoirs and other low-lying regions. The floods were spatially stable but varied in size and intensity from year to year with seasonal rainfall, hydrological conditions and surface runoff. The middle, south western and north western parts of FCT have been showing increased amount of inundation consistently indicating continued flood prone areas. In comparison, there was not much flooding in upland areas. The year-to-year changes noted during the six-year period indicates that flood occurrence in the FCT is recurrent and spatially concentrated. It alludes to the need for improved flood risk management, better drainage infrastructure and land-use planning in sensitive locations.

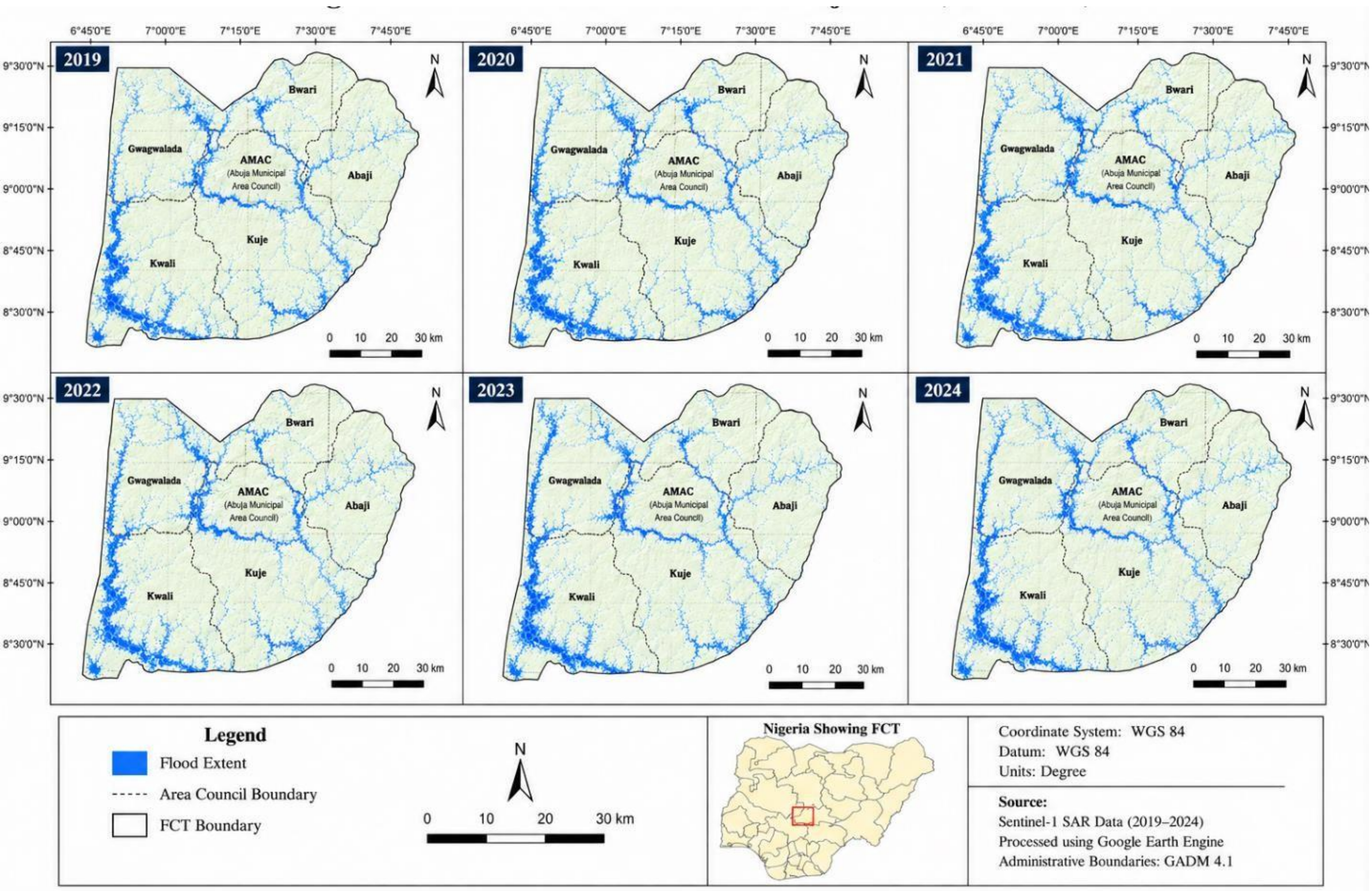


**Figure 4:** Annual flood extent in the FCT (2019 - 2024)

**Source:** Sentinel-1 Synthetic Aperture Radar (SAR) imagery

### Flood percentage

Figure 5 shows the flood percentage map that depicts the relative frequency of flood occurrence, therefore giving a long-term view of flood susceptibility in the FCT over the 2019–2024 research period instead of the condition in a single year. The higher percentages of flooding are largely concentrated along the main river corridor and adjacent floodplain ecosystems, indicating these areas were repeatedly swamped throughout the six-year period. By contrast, many areas within the study region showed low percentages of flooding, indicating that flooding either occurs infrequently, or that no detectable inundation occurred during the observation period. The spatial pattern indicates that the flooding in the FCT is not randomly scattered but highly associated with developed hydrological systems and low-lying terrain. The high concentration of flood zones with a high proportion in the same riverine habitats as the yearly flood maps indicates the durability of the flood-prone regions along time. Thus, the fundamental causes of flooding are the persistent physical features of the drainage configuration, the topography and the form of the river, not the specific annual weather phenomena that cause them. In terms of flood risk management, the flood percentage map provides a more reliable basis to identify chronic flood hotspots than single annual flood maps, as it reflects the cumulative flooding pattern over multiple years. Therefore, flood-prone areas should be targeted for floodplain protection, drainage improvements, infrastructure resiliency and land-use management to mitigate long-term flood susceptibility. The picture also shows the capability of the multi-temporal Sentinel-1 SAR and Google Earth Engine method to adequately identify persistent flood susceptibility patterns that can inform evidence-based urban planning and catastrophe risk reduction in the Federal Capital Territory.

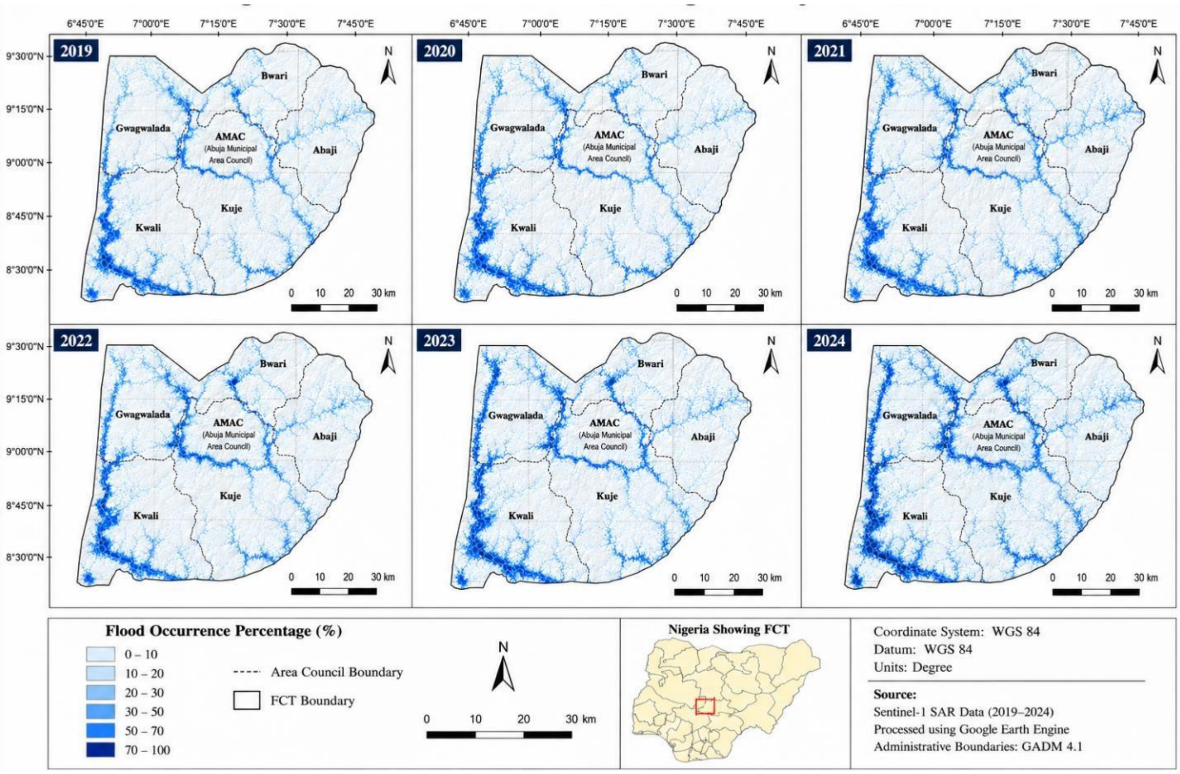


**Figure 5:** Flood Percentage in the FCT (2019 - 2024)

**Source:** Sentinel-1 Synthetic Aperture Radar (SAR) imagery

### Persistent Waterlogging (2019–2024)

Figure 6 shows the waterlogging persistency map that displays the areas where surface water persisted for the full study period 2019–2024. High persistence is often confined to major river systems and related floodplain habitats, providing a record of locations of prolonged or recurring water accumulation. In contrast, the low persistence levels in most sections of the FCT shows that the floods occurring in those locations are of seasonal and temporary character. The regional distribution of the results shows the places more prone to long term drainage difficulties that can have impact on infrastructural, agricultural and urban growth. Thus, the map is of tremendous value in the prioritisation of drainage improvement, floodplain control and sustainable landuse planning in the Federal Capital Territory.

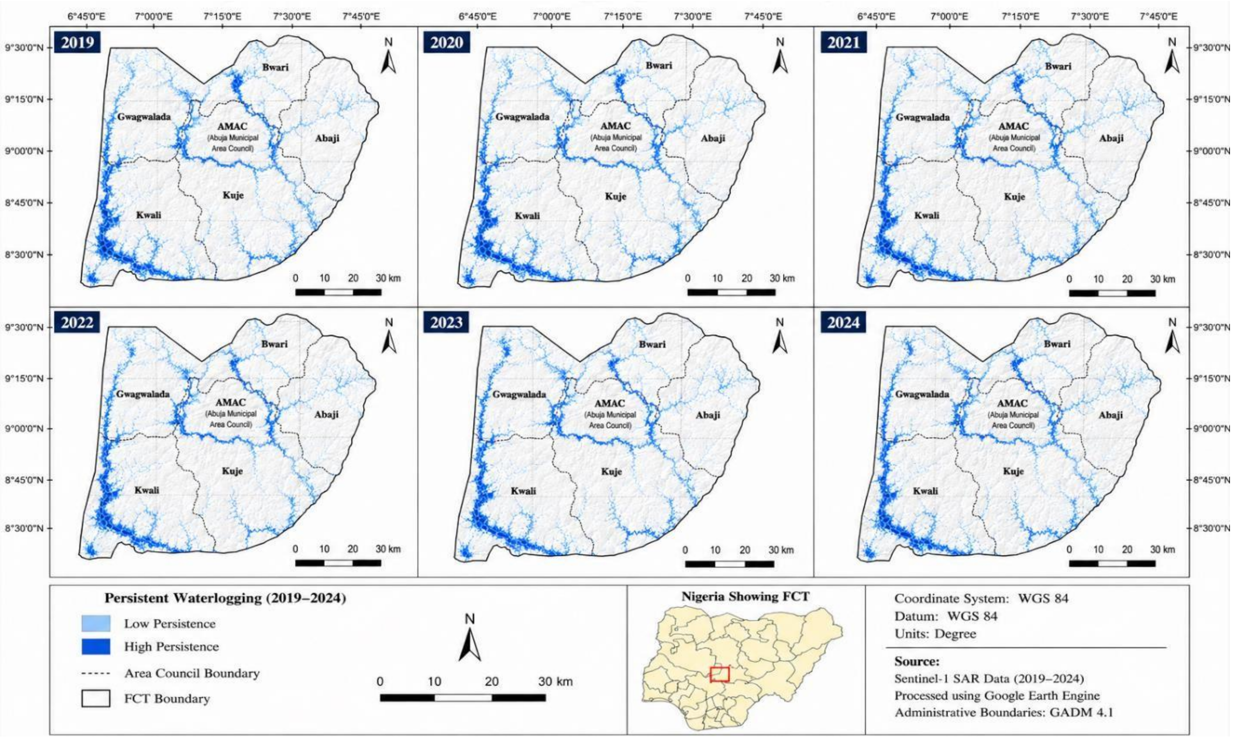


**Figure 6:** Persistent Waterlogging Areas in the FCT (2019 - 2024)

**Source:** Sentinel-1 Synthetic Aperture Radar (SAR) imagery

**Temporal variation in annual flood extent**

Figure 7 shows the FCT Annual Flood Extent Time Variation (2019-2024). The result shows a minor change from the year to the year with the flood area between ~39.98km$^2$ in 2021 to 40.66km$^2$ in 2022. But the general pattern was very steady during the period of research. Flooding, then, is defined by periodic inundation of existing flood-prone ecosystems, not by massive annual expansion. The temporal consistencies also corroborate the findings of the geographical study and emphasise the persistent hazard of flooding in the major river systems and their adjacent floodplains inside the FCT.

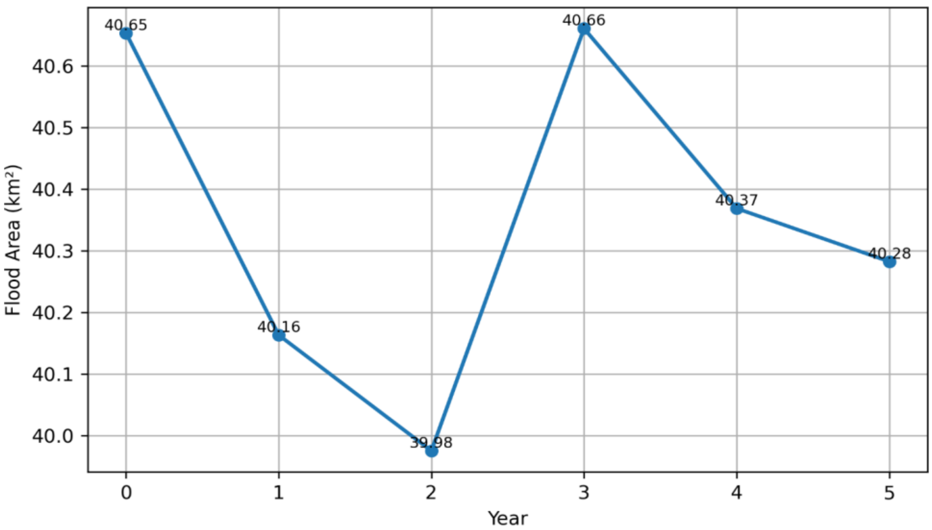


**Figure 7:** Annual flood area trend in the FCT (2019 - 2024)

**Source:** Sentinel-1 Synthetic Aperture Radar (SAR) imagery

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### Annual distribution of Sentinel-1 SAR images

Figure 8 depicts the Yearly distribution of Sentinel-1 SAR images used in the flood mapping methodology. The inventory has constant picture acquisition during the study period 2019–2024, providing appropriate temporal coverage to produce seasonal composites and annual flood maps. With several observations per year, the multi-temporal analysis was more reliable, decreasing the effect of single dates of acquisition and better representing seasonal flood conditions. The constant time coverage offered a good dataset for annual flood assessment, flood frequency analysis and identification of persistent flood prone locations within the FCT. Thus, the image inventory brings stability and repeatability to the established Google Earth Engine-based flood mapping procedure.

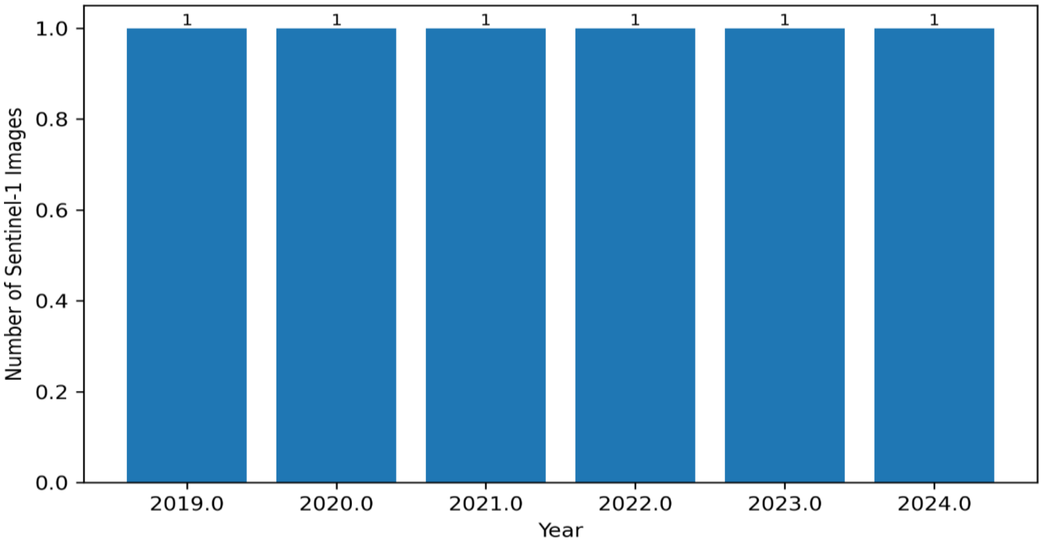


**Figure 8:** Sentinel-1 Image Inventory (2019 - 2024)

**Source:** Sentinel-1 Synthetic Aperture Radar (SAR) imagery

## DISCUSSION

### Temporal Dynamics of Flood Extent in the FCT

Multi-temporal SAR analysis showed that, although there was a very low interannual variation in the total area flooded in the FCT, the spatial persistence of flood occurrence during the six-year observation period was maintained. The expected flood extent was found to vary between 39.98 km2 in 2021 and 40.66 km2 in 2022. However, the fluctuation was less than 2% across the duration of study. The results do not show any significant variation in the behaviour of the flood but rather show that the occurrence of floods in the Federal Capital Territory is dominated by rather stable environmental parameters including drainage arrangement, floodplain morphology and terrain elevation. Thus, seasonal change in rainfall does not seem to have any effect on the extent of floods, the underlying geographical pattern being quite stable (Akintola, 2024). This is an important observation particularly as the flood management strategies of many emerging cities are founded on the concept that the yearly flood behaviour varies substantially from year to year (Garg *et al.*, 2024). Contrary to this assumption, the most vulnerable locations were not significantly altered during the research period. This persistence suggests that the flood risk in the FCT is closely related to the permanent landscape characteristics rather than only to the ephemeral hydrological circumstances. The results are therefore similar to Okodua *et al.* (2024) who have shown that Sentinel-1 SAR imaging is able to dependably capture periodic flood patterns in well established riverine systems, and radar observations are mostly insensitive to climatic variables. Tupas *et al.* (2024) and Zhao *et al.* (2024), show that a high frequency of floods is generally associated with stable floodplain ecosystems, where terrain and drainage have more influence than inter-annual climate variability. The current study extends prior findings to indicate the persistence of similar flooding inside the heavily urbanised landscape of the FCT. Long term flood danger maps may therefore be more informative for planning purposes than only using the estimates of single flood events.

### Spatial Characteristics of Flood Distribution

The spatial distribution of flooding revealed a clear concentration of inundation in the main river corridor and related flood plain settings, with the higher elevations of the FCT mostly unaffected throughout the study period. The distribution of floods over the land is controlled by the prevalence of natural drainage systems. The isolated clusters of floods in the north-eastern section also indicate the presence of small topographic depressions and weak drainage systems which can retain surface runoff during heavy rains. An important outcome from these findings is that flood episodes in the are not randomly dispersed in space (Cao *et al.*, 2023). Flooding happens through predictable hydrological pathways that are pretty constant over time. The spatial persistence indicates that proactive flood mitigation is achievable by identifying areas of repeated flooding prior to subsequent flood events. Thus, flood mitigation resources can be concentrated on places that are always most vulnerable to flooding, instead of being scattered evenly throughout the area. Similar spatial tendencies were reported by Giannone *et al.* (2024) who stated that river morphology and floodplain structure are the main controls on the inundation pathways in urban and rural catchments. Likewise, Zhuang *et al.* (2024) used Sentinel-1 SAR imagery to measure flood extent in complex riverine environments often difficult to characterise with optical sensors due to cloud cover. The results of the present study corroborate previous findings and confirm the reliability of SAR observations for detecting repeated flood-prone locations, pointing out its usefulness to support spatial planning in fast increasing metropolitan areas.

### Evaluation of the Google Earth Engine SAR Workflow

One of the main contributions of this study is the successful integration of Sentinel-1 SAR imagery in the Google Earth Engine cloud-computing environment to produce an automated approach for annual flood monitoring. The analysis of 349 Sentinel-1 scenes within a single computational framework highlights the potential of cloud-based geospatial platforms to enable large scale environmental investigations that would otherwise require significant processing resources (Ghosh *et al.,* 2023). Unlike many past studies of flood mapping that need manually determined classification criteria, the current approach used adaptive Otsu thresholding to define annual flood thresholds objectively. This strategy reduced the subjectivity of the operators and allowed the categorisation to adjust to the inter-annual variability of the features of the radar backscatter. This co-occurrence of permanent water masking and topography-based filtering further reduced the chance of misclassifying perennial water bodies or steep terrain as seasonal inundation and contributed to greater consistency in yearly flood classifications. The results are in accordance with the findings of Gorelick *et al.* (2017) who showed that the usage of Google Earth Engine substantially improves efficiency and reproducibility of large-scale geospatial analysis. Kumar and Mutanga (2023) highlight that cloud-computing platforms are allowing operational environmental monitoring via quick processing of multi-temporal satellite archives. But the present research points to a major practical limitation, too. However, resource limitations are an operational consideration for large scale SAR analyses, as illustrated by the project constraints imposed by Earth Engine's non-commercial computational quotas during processing, which affected export performance, regardless of the fact that cloud computing greatly enhances analytical capability.

### Implications for flood risk management and sustainable urban planning

Chronic flood-prone locations identification provides useful information for flood risk management in the FCT. The six-year observation showed multiple inundation in spatially comparable locations, which means structural and non-structural mitigation actions should largely focus on these recurrent hotspots. Therefore, investment in drainage improvements, flood retention infrastructure and river corridor management are more likely to deliver larger long-term benefits than reactive responses to specific flood events (Akintola, 2024). Urban planning data reveal severe challenges associated with continued growth in naturally inundated floodplains. The rate of urbanisation in the FCT is on the increase and encroachment of flood prone areas may increase the vulnerability of infrastructure and expose more people to flood hazard. Hence, the application of flood susceptibility data in land use planning, environmental impact assessment and infrastructure designing should be advocated for sustainable development of urban areas. The flood frequency products produced in this study offer solid evidence to identify locations needing development limits, improved drainage standards, and long-term resilience planning. This is consistent with the IPCC (2022) finding that enhanced forecasting and integration of spatial hazard information in planning decisions are essential for climate resilience. According to UNDRR (2022), the major way to reduce future disaster losses is risk-informed urban development. This paper presents real geographical evidence to assist international policy aims, by identifying chronic, not episodic, flood-prone zones.

## CONCLUSION AND RECOMMENDATIONS

### Conclusion

This project created and implemented a multi-temporal flood mapping workflow using Sentinel-1 Synthetic Aperture Radar (SAR) imagery in the FCT using the Google Earth Engine (GEE) platform. The study produced annual flood maps and identified persistent flood-prone locations from 2019 to 2024 by combining seasonal compositing, adaptive Otsu thresholding, permanent water masking, terrain filtering and flood frequency analysis. The workflow proved the potential of cloud-based geospatial processing for efficient analysis of huge SAR datasets while generating consistent and reproducible flood outputs. In accordance with the first objective, the study was able to successfully map the annual spatial distribution of floods in the FCT. The results indicated that flood occurrence was mostly localised around the main river corridors and associated floodplain settings whereas there was little or no inundation in the elevated locations. This demonstrates that the drainage pattern, the topographical features and the floodplain morphology are substantially determinant of the occurrence of floods in the territory.

Regarding the second aim, the temporal analysis indicated that the annual flood extent was reasonably consistent during the study period with minor variations in the range of 39.98 km 2 and 40.66 $km^2$. The consistency of inundation in identical spatial places despite slight annual variations shows that the occurrence of floods in the FCT is recurrent rather than sporadic events. The derived flood frequency products further proved the presence of persistent flood prone zones that need ongoing surveillance and intervention. The third objective was achieved by demonstrating that the established SAR-based process provides a robust and efficient approach for operational flood monitoring. Adaptive thresholding combined with landscape and permanent water masking reduced subjectivity in flood detection and enhanced consistency in classification. Furthermore, the use of Google Earth Engine improved the efficiency of the processing by utilising cloud-based analysis of multi-temporal Sentinel-1 images.

### Recommendations

The results of this inquiry lead to the following recommendations:

1. The physical planning authority shall include the identified flood prone and high frequency inundation areas in land use planning and development management. This will reduce the frequency of repeated floodplain conditions and reduce the future susceptibility of infrastructure and communities to flood threats.
2. Continuous flooding along major drainage corridors implies a need for continuous investment in drainage improvement, channel maintenance and storm water management infrastructure. Concentrate on flood-prone areas.
3. Relevant agencies such as the Federal Capital Development Authority (FCDA), Federal Ministry of Water Resources and Sanitation and National Emergency Management Agency (NEMA) should use Sentinel-1 SAR and Google Earth Engine into their routine flood monitoring programmes. This would facilitate the speedy and objective assessment of flooding; particularly where long-term cloud cover limits the use of optical imagery.

### Practical Implications of the Study

This study provides practical contributions to flood risk management, urban planning and geospatial decision making in the FCT. This study demonstrates the capability of the cloud-based Google Earth Engine process to integrate Sentinel-1 SAR data with adaptive Otsu thresholding, terrain filtering and permanent water masking to offer a cost-effective and reproducible solution for long term flood monitoring in data scarce environments.

That is unlike traditional flood mapping using field observations or cloud sensitive optical imagery. The proposed flowchart guarantees the consistency and timeliness of flood information because floods may be reliably recognised under various weather circumstances.

Identifying chronic flood prone areas provides spatially explicit data for decision makers to prioritise flood prevention. The generated flood frequency and annual flood maps can be used by Government Agencies such as Federal Capital Development Authority (FCDA), National Emergency Management Agency (NEMA), Federal Ministry of Water Resources and Sanitation and FCT Emergency Management Department (FEMD) in support of floodplain zoning, infrastructure planning, emergency preparedness and land use regulation. The results also provide helpful information for engineers and urban planners constructing highways, bridges, drainage systems and residential buildings in flood-prone areas. Furthermore, the presented methodology provides a realistic framework that may be applied in other states of Nigeria and cities of sub-Saharan Africa facing similar challenges of rapid urbanisation, inadequate hydrological data and persistent cloud cover. The cloud-based technology removes computational barriers and provides a route for institutions with low computing resources to use better flood monitoring, thus enabling evidence-based environmental management and climate adaptation planning.

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