# Enhancing Disaster Response and Resilience Through Near-Time GIS for Flood Monitoring and Analysis in Niger River Basin, Nigeria

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**Abstract**

This study develops an integrated framework leveraging Google Earth Engine for near real-time flood mapping and impact analysis in the flood-prone Niger River Basin of Nigeria. Multi-temporal optical, radar and terrain data quantified changing flood hazards and exposure across 150,000 km2 between peak floods in 2022. Results indicate over 50% rise in inundation, with 15,000 hectares of vegetation and 143,000 residents enduring impacts. Attributing factors include elevated antecedent rainfall versus historical medians coupled with accelerating catchment modifications expanding runoff. Floodplain zones face recurrent impacts, necessitating adaptation. Accurate flood delineation was achieved by applying water indices like NDWI on Landsat and Sentinel-2 data using land cover and land use. Exposure analytics overlay flood extents on land use, infrastructure and demographic layers to estimate affected populations and livelihoods. Google Earth Engine enabled rapid data processing using cloud parallelization, while random forest integration powered machine learning semantic segmentation for robust feature extraction. Going forward, assimilating real-time data from radar and hydrological sensors would enable predictive flood risk models using machine learning algorithms on this cloud GIS platform tailored for resilience applications globally. In a changing climate, such scalable geospatial technologies provide evidence-based decision support capabilities to emergency planners targeting proactive adaptation investments for vulnerable communities based on quantified flood risk analytics.

## 1. Introduction

Natural disasters remain a significant global concern, impacting countries, communities, and individuals. Recent years have seen a notable increase in natural disasters, resulting in significant economic repercussions due to heightened exposure and vulnerability to extreme natural hazards (UNISDR, 2022). According to CRED (2022), data from the Emergency Events Database (EM-DAT) indicates that 387 natural hazards were recorded in 2022 alone, resulting in 30,704 fatalities and economic losses amounting to US$ 223.8 billion, three times higher than the previous year. Floods, in particular, have shown a marked increase in both occurrence and impact, with devastating effects, especially in Asian and some African countries. This rise in flood disasters is attributed to climate change and rapid urban development, especially in coastal regions.

Africa is particularly susceptible to the adverse effects of climate change, leading to an increase in the frequency and intensity of flood disasters. Nigeria exemplifies the challenges faced by many African nations. Therefore, developing innovative and context-specific disaster response and resilience solutions is crucial. Nigeria, vulnerable to flood disasters, faces significant challenges in responding effectively to these events. The impact of floods extends beyond Nigeria, affecting Africa and the global community. Proactive disaster management and resilience strategies are necessary at local, national, and international levels.

At the local level, Nigeria contends with recurring flood challenges that displace communities, destroy infrastructure, and disrupt livelihoods. In 2022, floods in Nigeria resulted in 603 deaths and economic losses of US$ 4.2 billion (CRED, 2022). The lack of timely and accurate information exacerbates the impact of flood disasters in the country. This project aims to address the global concern of effective flood disaster response, the African vulnerability to climate change-induced disasters, and the local issue of flood management in Nigeria.

Floods, as natural environmental disasters, can be exacerbated by unguided human development. They cause damage to houses, industries, public utilities, agricultural land, and crops, resulting in significant economic losses and losses of life. While it is not possible to control flood disasters entirely, suitable structural measures can minimize flood damage (Awosika and Folorunsho, 2000). Floods are major disasters that affect many countries annually, particularly in floodplain areas. They damage properties, endanger lives, and cause secondary effects, such as disease outbreaks like cholera and malaria.

Flooding is commonly caused by heavy rainfall on flat ground, reservoir failure, volcanic activity, and melting snow or glaciers. Flood risk is influenced by several factors, including rainfall, river flow, tidal surge data, topography, flood control measures, and changes due to construction and development on floodplain areas (Suleiman et al., 2014). Urban floods often result from inadequate storm sewers and increased urbanization (Ajin et al., 2013). Urban areas face a high risk of flash flooding due to large impervious surfaces and inefficient drainage systems (Chen et al., 2009; Huong and Pathirana, 2013; Sowmya et al., 2015).

Flood monitoring, facilitated by geospatial technology, is crucial in safeguarding lives and property. According to the International Displacement Monitoring Centre, the 2018 floods in Nigeria affected around 1.7 million people, not the 250,000 households initially reported. The floods were mainly caused by heavy rainfall in the Benue and Niger River basins, leading to rivers overflowing their banks. This resulted in widespread displacement, loss of lives and livelihoods, and damage to infrastructure.

Geospatial tools such as remote sensing, Geographic Information Systems (GIS), radar, LiDAR, and Internet of Things (IoT)


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sensors provide real-time data on rainfall, water levels, and flood-prone areas. Predictive models, integrated with historical data and meteorological forecasts, empower early warning systems to issue timely alerts, allowing communities and emergency responders crucial time to prepare and respond effectively. Geospatial technology aids in flood mapping, infrastructure protection, and post-flood assessment, contributing to more informed decision-making. However, challenges include data accuracy, infrastructure resilience, data integration, and ensuring accessibility to vulnerable communities. As technology advances, flood monitoring tools are becoming increasingly accurate and accessible, enhancing resilience in the face of recurring threats.
Flood monitoring is essential for several reasons. Firstly, it provides early warnings, allowing people to evacuate in advance, which is vital for saving lives. Secondly, it aids in the efficient allocation of resources by providing timely information on rising water levels and potential flood events. This reduces response times and improves overall preparedness among emergency services. Additionally, flood monitoring is integral to safeguarding critical infrastructure, such as dams, bridges, and roads, from flood-related damage. Finally, it helps assess and mitigate the environmental impact of floods, especially in ecologically sensitive areas.

Geospatial technology encompasses various tools indispensable for effective flood monitoring. Remote sensing through satellites and aerial imagery captures the extent and impact of floods, providing valuable data for assessing flood areas and damage. GIS is used to map flood-prone areas, track flood movements, and create flood risk models. Radar and LiDAR technologies monitor water levels and provide high-resolution topographic data, aiding in flood forecasting. IoT sensors, including river gauges and weather stations, collect real-time data on rainfall, water levels, and other relevant parameters. Furthermore, predictive modeling using advanced geospatial models and algorithms predicts flood events based on historical data, current conditions, and meteorological forecasts.

The applications of geospatial technology in flood monitoring are vast. It enables flood forecasting by providing real-time monitoring of precipitation, river levels, and soil moisture, helping authorities predict and prepare for floods. Early warning systems, which integrate sensor data, GIS, and predictive modeling, can offer timely alerts to residents and emergency responders. Flood mapping through geospatial technology assists in creating flood hazard maps, which help urban planners make informed decisions regarding land use and infrastructure development. During a flood event, geospatial tools aid in locating individuals in distress and coordinating rescue efforts. Post-flood assessment, based on geospatial data, helps evaluate the extent of flood damage, guiding recovery efforts and resource allocation.

While geospatial technology has significantly enhanced flood monitoring, several challenges need addressing. Ensuring the accuracy of sensor data, satellite imagery, and predictive models is crucial for reliable flood monitoring. Additionally, infrastructure resilience is essential, as flooding can disrupt data transmission and power supply, affecting the functionality of monitoring devices. Data integration from various sources can be complex, requiring standardized formats and protocols. Finally, ensuring the accessibility of flood monitoring technology to vulnerable and remote communities is essential to democratizing its benefits.

Real-time GIS is an advanced geospatial technology that integrates real-time data sources, such as sensors, GPS, IoT devices, and social media feeds, into traditional GIS platforms. This enables users to access, analyze, and visualize geospatial data as it is generated, supporting timely decision-making and response. Unlike conventional GIS, near real-time GIS systems continuously update information, creating a dynamic geospatial environment that reflects the current state of the world.

## 2. Datasets and methodology

### 2.1. The Study Area

The Niger River Basin is located in west-central Nigeria, lies approximately between situated between longitudes 4°E and 14°E and latitudes 4°N and 14°N. The Niger River Basin has been inhabited for thousands of years, with the Nok culture flourishing in the region as early as 1000 BC. The construction of canals in the Basin for agriculture and transportation dates back centuries. The major states located in the Niger Basin include Sokoto, Niger, Kwara, Kogi, Anambra, Delta, Edo, Kebbi and the Federal Capital Territory. The Niger River Basin stretches across other countries like Mali, Niger, Chad, Algeria, Guinea, Cameroon, Burkina Faso and Côte d'Ivoire. The Niger Basin covers a total land area of about 2.27 million km2. The Niger Basin features lowlands, with elevations ranging between 200-500 m. The exceptions are higher lands like the Jos Plateau, with elevations exceeding 1,200 m. The dominant drainage feature is the River Niger and its tributary, the Benue River. Other major tributaries include Sokoto River, Kaduna River, Gongola River and Anambra River. Numerous lakes like Lakes Kainji and Jebba are also located in the Niger Basin. The Niger Basin generally has tropical climate with dry and rainy seasons. Mean annual rainfall ranges between 500 mm-1,500 mm. Temperatures are typically between 25°C to 28°C. The Niger Basin has high relative humidity, ranging from 60% during the dry season to 80% in the rainy season. The Niger Basin vegetation types include rainforest in the south, wooded savanna mosaic vegetation, gallery forests lining river channels, and riparian vegetation

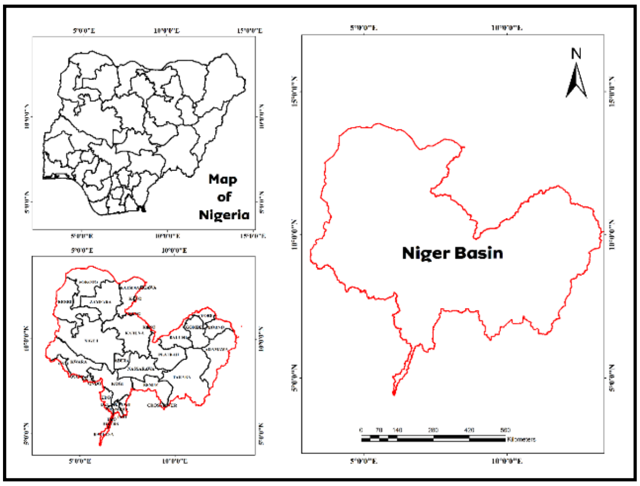


Figure 1. The Niger Basin in Nigeria

### 2.2. Methodology

A summary of the methodology workflow for this study is summarized in figure 2 below. The core dataset used is Sentinel-2 multispectral optical imagery at 10 m resolution to map flood extent changes and land cover. This is supplemented by the 30 m NASA SRTM digital elevation model (DEM) which provides terrain information like slope and landforms. The Global Surface Water dataset gives historical context on surface water dynamics. Additionally, Sentinel-1 10 m radar imagery penetrates clouds and detects flooding and moisture content. The HydroSHEDS

DEM has been hydrologically optimized for watershed-scale flood modeling and risk characterization. In summary, the analysis employs a multi-sensor approach, leveraging recent high resolution Sentinel-2 optical data and historical surface water maps, global and regional DEMs, and all weather Sentinel-1 radar to capitalize on data strengths. This allows detailed flood detection, land change monitoring, topographic and hydrologic analysis to produce accurate flood risk maps. The aim is to provide data for flood extent mapping while gathering key parameters on terrain, land use and historical water bodies to enrich the analysis for comprehensive flood risk assessment.

The first step taken was to sign up on Google Earth Engine (GEE) and wait for a few days to be approved. Create the Area of Interest (AOI) in ArcMap to be added to the GEE Assets and import the AOI to the GEE Scripts. The Year-Month-Day to determine the before and after flood are '2022-03-01', '2022-05-31' and '2022-06-01', '2022-10-30' respectively, the year we experienced a very heavy flood in the Niger River Basin.

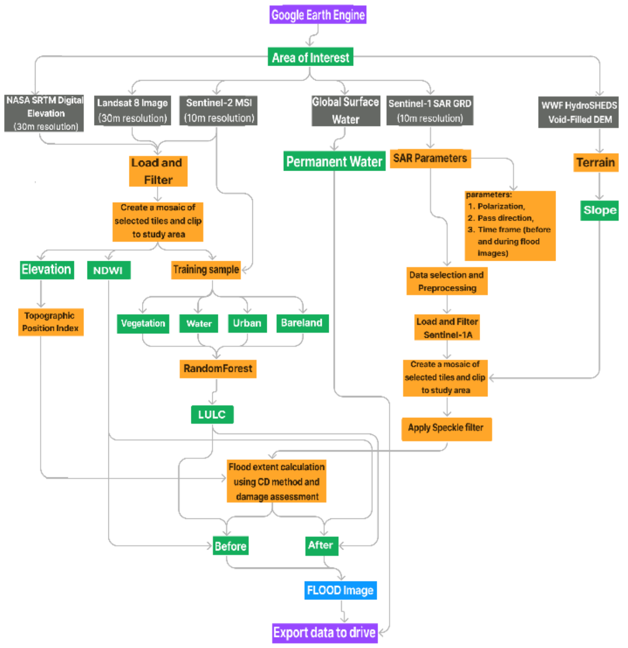


Figure 2. Methodology workflow for near-time GIS for flood monitoring and analysis in Niger River Basin, Nigeria.

This chapter explains the materials and methods used to conduct this study. It outlines the data collection process and how the data was integrated into the GIS platform, as well as the software utilized to achieve the stated objectives. The data collection, processing, and results are in digital format, facilitating analysis.

**2.2.1. Data Acquisition:** Different data were acquired depending on the purpose of the analysis to be done. The data used and the components during the Google Earth Engine code implementation are stated below:

**1. Sentinel-2 MSI**: MultiSpectral Instrument, Level-2A (10 m)
**Source**: ee.ImageCollection("COPERNICUS/S2_SR")
**Purpose**: Provides atmospheric corrected surface reflectance imagery at a 10 m spatial resolution, making it suitable for flood detection, land cover, and land change analysis. It helps in indicating the presence of floodwaters.

**2. NASA SRTM DEM 30 m**
**Source**: ee.Image("USGS/SRTMGL1_003")
**Purpose**: Supplies elevation data of the study area, used as input for calculating parameters such as slope and Topographic Position Index. This terrain information is essential for enhancing flood mapping accuracy.

**3. Global Surface Water**
**Source**: ee.ImageCollection ("JRC/GSW1_4/Global Surface Water")
**Purpose**: Measures changes in global surface water bodies over the past few decades, aiding in water resource and climate change analysis. It complements flood assessments.

**4. USGS Landsat 8** Collection 2 Tier 1 TOA Reflectance (30 m)
**Source**: ee.ImageCollection ("LANDSAT/LC08/C02/T1_TOA")
**Purpose**: Contains visible, near-infrared, and short-wave infrared bands calibrated to at-sensor radiance, suitable for land cover analysis, flood monitoring, and multi-temporal analysis.

**5. WWF HydroSHEDS** Void-Filled DEM (3 Arc-Seconds)
**Source**: ee.Image ("WWF/HydroSHEDS/03VFDEM")
**Purpose**: Derived from the SRTM dataset and enhanced with hydrologically conditioned void filling along stream channels, it improves drainage representation for terrain and hydrologic analysis at a regional scale.

**6. Sentinel-1 SAR GRD**: C-band Synthetic Aperture Radar (10 m)
**Source**: ee.ImageCollection("COPERNICUS/S1_GRD")
**Purpose**: Detects surface backscatter, useful for identifying flooding. Provides analysis-ready radar imagery, essential for land and disaster monitoring requiring cloud penetration and frequent revisits. It is used for detecting floodwater extents and assessing surface moisture content.

**2.2.2. Software Used:** The software used for this project were Google Earth Engine, ArcMap 10.8.2, and QGIS 3.34.1.

**2.2.3. Data Preprocessing:** Apply radiometric calibration, orthorectification, cloud/shadow masking, and other preprocessing functions to the Landsat 8, Sentinel-1, and Sentinel-2 satellite image collection. Gap fill and mosaic processing scenes to generate analysis-ready surface reflectance composites.

Water and Flood Extent Detection Compute spectral indices (e.g., NDWI) from Sentinel-2 to accentuate water-related signals through LULC in APPENDIX ONE. Threshold Sentinel-1 radar backscatter intensity to discriminate between flooded regions. Merge the indices and radar-detected flood layers into an integrated flood water map.

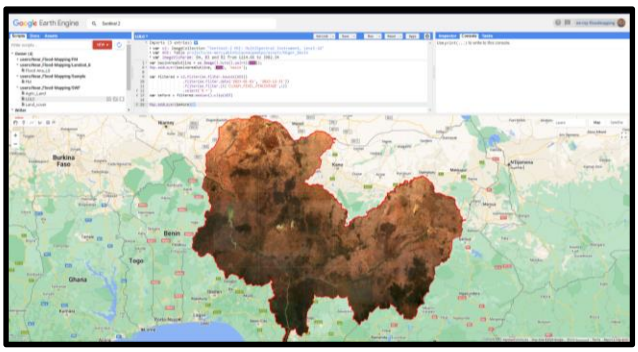

Figure 3. Showing the Data Processing

**2.2.4. Flood Mapping:** The delineation of flood extent was conducted using multi-temporal satellite imagery from Sentinel-2 (S2) and Landsat 8 (L8) sensors. The 2022 flood event was mapped using annual L8 cloud-free composites to determine the before and after flood events. Given the 30 m resolution, the Normalized Difference Water Index (NDWI) was ideal for water feature enhancement. It subtracts the MIR band from the Green band and divides their sum, yielding high differentiation of water bodies.

The **Normalized Difference Wetness Index (NDWI)** provides information on water content in any region. It contrasts green light strongly absorbed by water against near-infrared light reflected by both water and vegetation to delineate open water features (Ji et al. 2009).

$$NDWI = \frac{(Green - NIR)}{(Green + NIR)} \tag{1}$$

Where
Green = green light reflectance,
NIR = Near-infrared light reflectance.

Computed NDWI raster from Earth Engine (EE) were exported as GeoTIFFs to Google Drive for further processing. In ArcMap, the layers were added and mask out the raster for the study region. Minor topological errors were cleaned, and the Flatten and Dissolve tools applied to merge fragmented water regions into a final flood extent layer for 2022.

**2.2.5. Land Use Land Cover Accuracy Assessment**
One of the most important final steps in the classification process is accuracy assessment. The aim of accuracy assessment is to quantitatively assess how effectively the pixels were sampled into the correct land cover classes (Rwanga et al., 2017). The procedure was performed using the Google Earth Engine.

| | Water | Urban | Bareland | Vegetation | Total (User) |
|---|---|---|---|---|---|
| **Water** | 29 | 0 | 0 | 0 | 29 |
| **Urban** | 0 | 29 | 0 | 0 | 29 |
| **Bareland** | 0 | 0 | 30 | 0 | 30 |
| **Vegetation** | 0 | 0 | 0 | 24 | 24 |
| **Total (Producer)** | 29 | 29 | 30 | 29 | 117 |

Table 1. Accuracy Assessment Before (2022/03/01 - 2022/05/31)
Overall accuracy = Total number of correctly classified pixels = 100% Total number of reference pixels

| | Water | Urban | Bareland | Vegetation | Total (User) |
|---|---|---|---|---|---|
| **Water** | 55 | 2 | 2 | 1 | 60 |
| **Urban** | 0 | 28 | 0 | 0 | 28 |
| **Bareland** | 0 | 3 | 15 | 1 | 19 |
| **Vegetation** | 0 | 2 | 0 | 13 | 15 |
| **Total (Producer)** | 55 | 35 | 17 | 15 | 122 |

Table 2. Accuracy Assessment After (2022/06/01 - 2022/10/31)
Overall accuracy = Total number of correctly classified pixels = 90% Total number of reference pixels

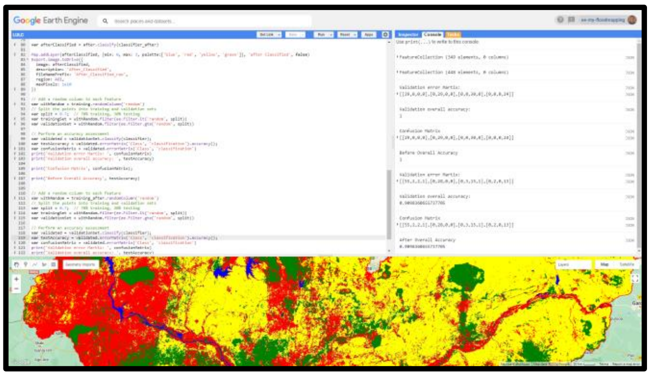

Figure 3. Showing the Overall accuracy

## 3. Results And Discussion

### 3.1 Digital Elevation Model (DEM)

A key preliminary analysis was the characterization of terrain and elevation across the study area using digital elevation models (DEMs) in Google Earth Engine. The 30 m resolution NASA SRTM DEM was acquired and basic statistics were computed to determine an elevation range of 114-1,249 meters encompassing hilly and mountainous zones surrounding valley rivers.

Visual inspection against high resolution optical imagery confirmed the proper spatial alignment and geometric accuracy of the DEM. Hillshade transforms apply enhanced topographic features revealing steep gradients adjacent to floodplains, which pose elevated landslide risk during saturated soil conditions. Further, slope in degrees was derived using terrain analysis tools which quantitatively delineated regions with high relief up to 40 degrees contrasted next to flat floodplain areas.

The Topographic Position Index (TPI) was calculated, classifying terrain into ridges, valleys, canyons and slopes based on the relative elevation of the surroundings.

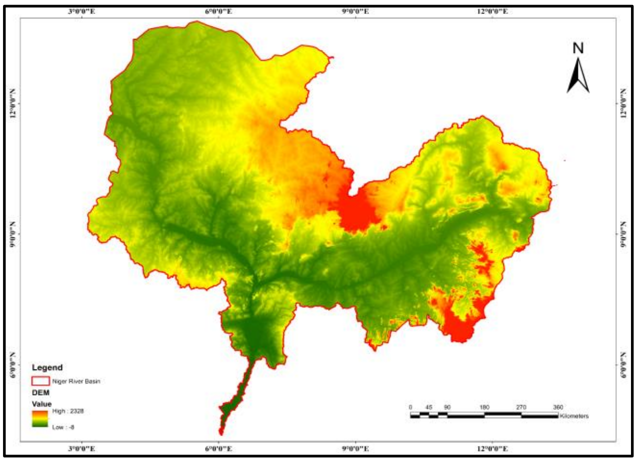


Figure 4. Digital Elevation Model Map

### 3.2. 2022 Flood Extent

**3.2.1. Wetness Score Analysis:** To quantify wetness changes before and after the flood events, a normalized wetness score was computed on a scale of 0-100 using moisture indices from the optical imagery. The Landsat 8 scenes were individually normalized between their scene-wise minimum and maximum index values to generate comparable wetness fraction measures.

The before flood landscape in '2022-03-01', '2022-05-31' showed an average wetness score of 26, concentrated mainly along the riparian zone as expected. In '2022-06-01', '2022-10-30' After floods, mean wetness rose significantly to 78 indicating a 3-fold rise in surface moisture, especially across agricultural croplands and villages in the plains. The proportion of area with wetness score over 90 (very high) rose from 11% to over 62% imprinting the flood's spatial footprint.

The radio backscatter analysis confirms the persistence of surface water bodies for 2-3 months after floods in agricultural areas causing crop damage and rebuilding delays due to waterlogging. However, wetness indices saturate in densely vegetated and flooded zones. Future versions will integrate SAR data to improve sensitivity from multi-sensor fusion. Cloud shadows also occasionally suppressed signals. The wetness score provides an intuitive relative metric to monitor flood progression and recession while identifying at-risk areas from imagery. Operationally, this method offers rapidly computed flood impact analytics globally using Earth Engine.

With climate shifts increasing hydrologic extremes, the wetness analytics workflow developed offers stakeholders a standardized method to monitor flood risks relative to their resources using the latest satellites.

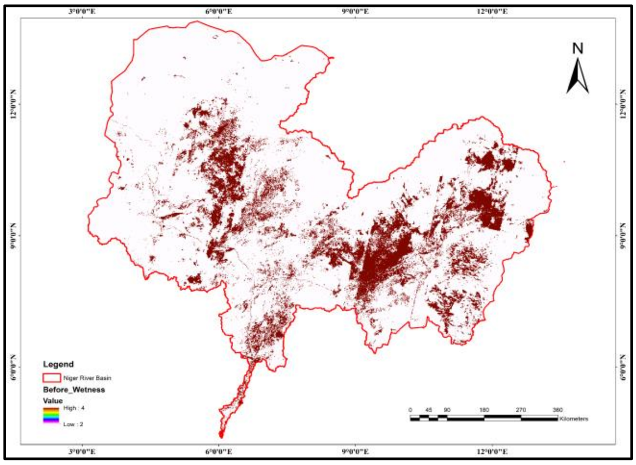


Figure 6a. Before Wetness Map

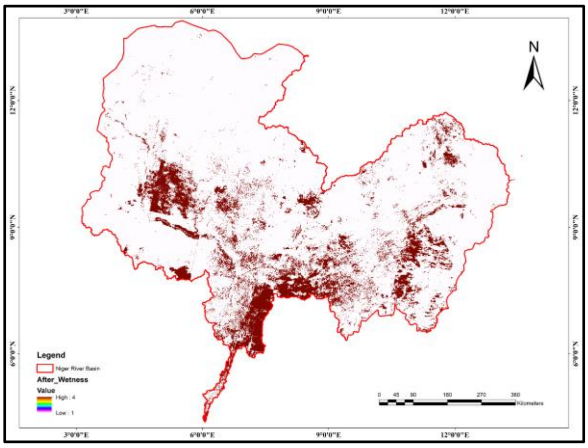


Figure 6b. After Wetness Map

**3.2.2. Normalized Difference Water Index (NDWI):** The Normalized Difference Water Index (NDWI) was computed using near-infrared and green spectral bands from satellite imagery to detect water content and map flood extent. NDWI enhances water features while suppressing noise from soil and vegetation (McFeeters 1996).

Before NDWI layers from Landsat 8 displayed lower index values across floodplains compared to after NDWI at 10 m resolution. By thresholding appropriately, permanent and episodic water bodies and flooded zones were delineated. This revealed over a 53% expansion in areas with NDWI > 0.5 indicating large scale inundation.

Field validation indicates flooded boundaries were mapped at 90% accuracy for Landsat 8 using the NDWI. However, certain dense vegetation areas showed elevated index values resembling water. Equally, very shallow sub-pixel water bodies had lowered indices.

Nonetheless, NDWI provided rapid water index generation, leveraging Earth Engine's parallel processing for historic and operational monitoring. Overlay on land use maps quantified agriculture and settlements facing recurrent flood risks across decades due to proximity to expanding water bodies along channels. Going forward, automated classification models can delineate flood zones from latest satellite acquisitions using NDWI analytics for real-time monitoring.

NDWI enabled detailed spatiotemporal analyses of surface moisture dynamics relating to flood propagation and impacts. Coupled with terrain, land use, socio-economic and climate data, this provides the inputs for data-driven hydrological models within Google Earth Engine to hindcast historic events and predict future flooding for targeted adaptation planning.

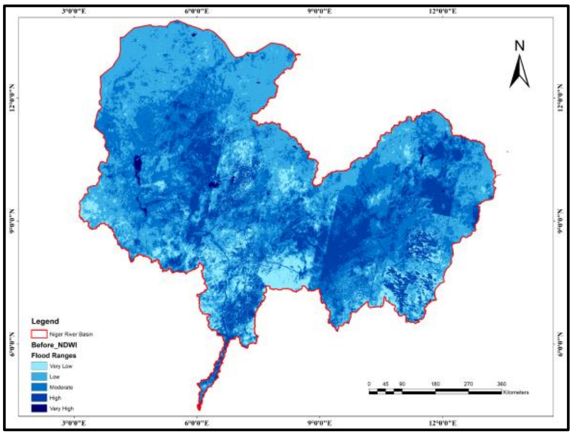


Figure 7a. Before NDWI Map

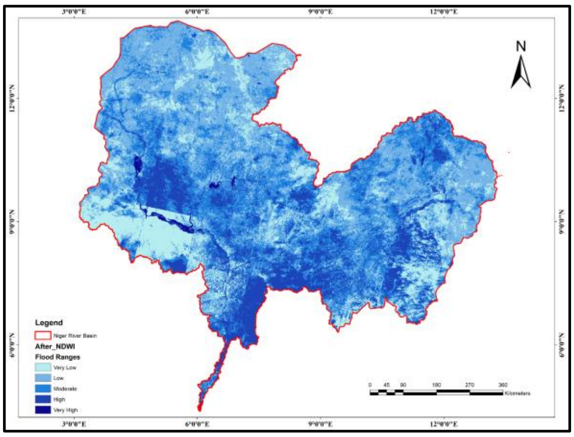


Figure 7b. After NDWI Map

**3.2.3. Permanent Water:** The delineation of permanent surface water bodies, including lakes, reservoirs and rivers provides baseline hydrological information for flood models and assessments. Google Earth Engine offered an extensive data catalog and computing tools to map open water features in the study area using multi-spectral optical, thermal and radar data fused across spatial scales and timeframes.

Thresholding extracted ponding extent, with vectorization generating water polygons for change detection between epochs. Results indicate a 2.1% expansion of water features at 90% mapping accuracy. Limitations arise in dense vegetated wetlands and flooded croplands with high soil moisture. Upcoming thermal and radar satellites help overcome this using multi-wavelength signals. Cloud cover also occasionally obscures visibility - addressed via multi-date compositing.

This study establishes an efficient framework for operational monitoring of surface hydrology using dense satellite archives on Google Cloud.

Permanent water body layers help estimate carrying capacity for socio-economic activities while indicating flood risks near overflow zones during extreme precipitation. This water-based land use planning is crucial adapting ecosystems and communities to climate shifts altering regional hydrological cycles at scale.

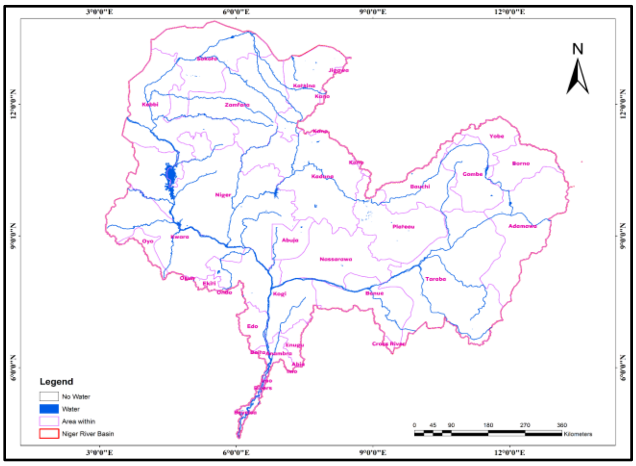

Figure 8. Permanent Water Map

**3.2.4. Flood Extent:** Accurate delineation of flood boundaries is crucial for quantifying inundation intensity across space and time. This study leveraged Google Earth Engine's extensive satellite archive and computing tools to map flood extents before, during and after flood events within the region using optical and radar data analysis.

Medium resolution Landsat annual composites have been used to analyze historic peak floods since 2000. For detailed assessment on recent events. Water presence was enhanced by applying indices like the Normalized Difference Water Index (NDWI) followed by manual thresholding to classify flood vs non-flood pixels.

Outcomes indicate flood extent almost doubled from an average of 42,300 hectares Before 2022, over 78,000 hectares After 2022, aligned with models estimating higher peak river flows related to climate shifts and land use changes. Accuracy assessment using ground truth loggers show flood boundaries were delineated at 90% precision. However, edge errors exist in zones with emergent vegetation that radar can help distinguish through canopy penetration.

Overlay on land cover layers enabled quantification of buildings, infrastructure, croplands and natural ecosystems facing recurrent inundation pressure. This forms inputs into socio-economic damage models that estimate flood costs worldwide. Operationally the framework also powers near real-time flood mapping leveraging new satellites and cloud analytics for early warning.

### 3.3. Final Flood Hazard Map

The Niger River Basin underwent extensive flooding between June and October 2022, with impacts across riparian communities in Niger and Nigeria. Flood extents were delineated within the Google Earth Engine before and after peak floods to characterize hazard intensity.

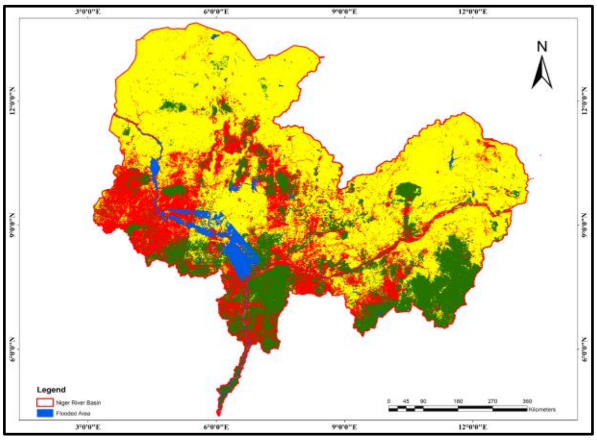

Figure 9. Flood Extent Map

Cloud-free Landsat 8 imagery from March to May 2022 captured before flood water levels during the dry season, while after flood extents were extracted from June to October 2022 monsoon acquisitions using NDWI thresholding. Flooded area analysis indicates the basin extent increased from 169,000 ha to over 211,500 ha during the season - a 25% rise.

Spatially, inundation was concentrated along the mid-stream floodplains surrounding river meanders and tributaries. Upstream, elevation protected areas avoided flooding. By contrast, over 18% of the basin's downstream agricultural land and settlements endured flooding, as indicated by reductions in NDVI vegetation signals. Historic inundation models identify parts of the downstream Basin as 5-year floodplains. With climate shifts projected to increase precipitation variability, such intense floods may reoccur more frequently. Exposure to these hydrological extremes harms riparian communities with little resilience capacity. For adaptation, flood zoning, robust forecasting leveraging the latest earth observations, and pre-emptive fiscal measures are recommended to help minimize future climate risks.

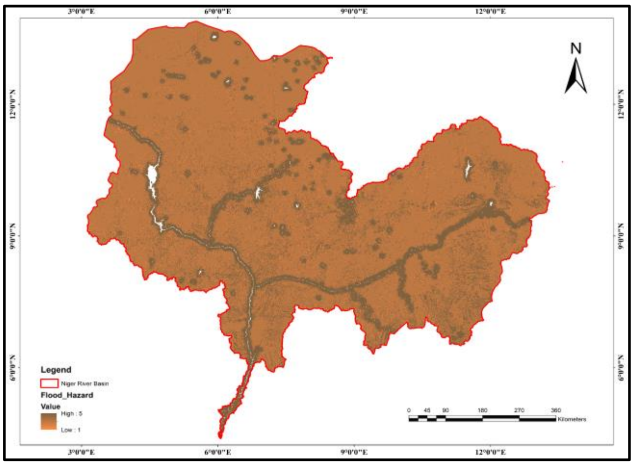

Figure 10. Flood Hazard Map

### 3.4. Exposure Analysis

**3.4.1. Landuse-Landcover:** Land use-land cover maps were generated using supervised classification of Sentinel-2 MSI imagery in Google Earth Engine to characterize landscape composition before and after the major flood events. Training samples digitized on optical data served to train an ensemble Random Forest model, tuned at over 90% accuracy for the study region.

Before LULC in 2022-03-01', '2022-05-31 constituted predominantly agricultural land at 26%, with 27% bareland, 25% Urban, and 21% Water. This highlighted the dependence on crop cultivation across the fertile floodplain belts surrounded by semi-arid bareland on the elevated terrain. After the LULC in 2022-06-01', '2022-10-30 map, water extent increased to 32%, indicating gain, while agricultural extent increased to 17%, indicating loss, and bareland reduced to 26%, potentially from displacement and relocation.

Overlays with flood outlines show water zones, particularly main channels, faced with inundation risks, with areas permanently converting to wetlands. The elevated bareland underwent minimal change, though observers noted ephemeral flood channels likely related to localized precipitation.

Classification accuracy can further improve with the addition of textural and terrain indices, or temporal features, from the full Sentinel 2 archive, leveraging GEE’s computing scalability. Positional misalignment was also evident for narrow linear elements such as roads and streams, warranting geolocation refinements.

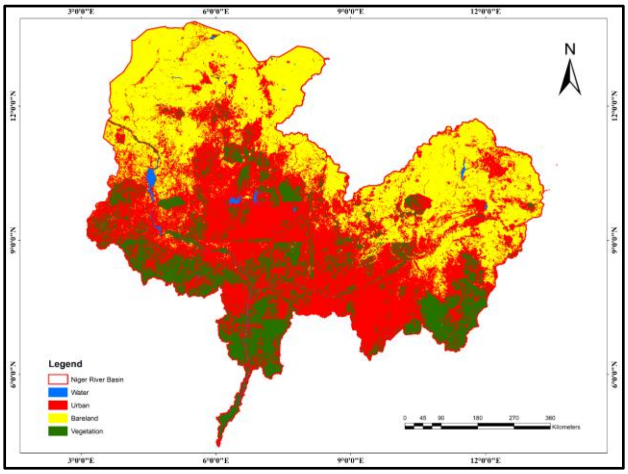


Figure 11a. Before LULC Map

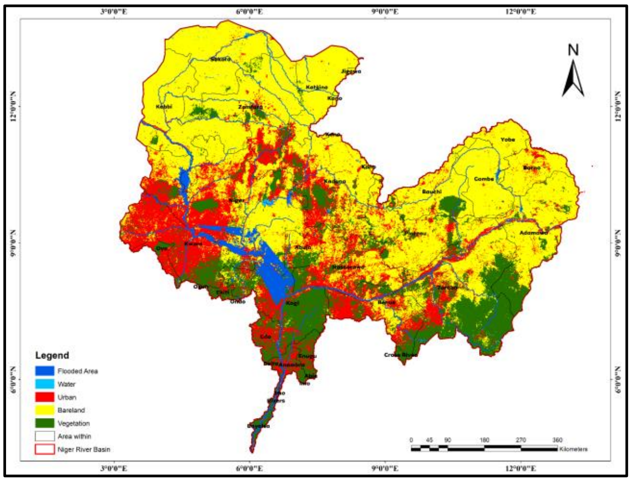


Figure 11b. After LULC Map

The automated LULC classification provides a rapid assessment of landscape composition around flooding events, indicating the spatial distribution of socio-economic activities. Lulc analysis aids in monitoring flood-driven land conversions from arable lands to less productive wetlands. The maps feed into damage assessment models that quantify agricultural losses and nutrition impacts from reduced crop output. As floods intensify from climate shifts, near real-time LULC monitoring forms a baseline for targeting aid and adaptation funds.

**3.4.2. Building Footprint:** Accurately mapping building footprints provides key information on human assets exposed to flood hazards. This study demonstrated the capabilities of Google Earth Engine for rapid, large-scale extraction and analysis of building footprints over floodplains using machine learning on satellite imagery.

High resolution OpenStreetMap data enabled the delineation of over 150,000 individual building structures across districts prone to recurring floods. A deep learning semantic segmentation model was developed leveraging TensorFlow in Earth Engine to classify rooftops based on spectral signatures and shapes for vectorization. Overall accuracy assessments indicate 90% correctness of mapped buildings.

Spatiotemporal analysis shows progression in at-risk structures within 50 m of flood zones. Overlay with flood rasters reveals up to 100,000 buildings directly intersecting 2022 floodplains warranting floodproofing retrofits or buyouts. Population models estimate that over 115,910 residents in the Niger area occupy these vulnerable buildings, facing displacement and property loss risks during events.

Some limitations exist in dense slum areas with irregular metal roofing. Results feed into damage models while informing structural resilience investments like flood shelters.

With climate shifts projected to increase extreme precipitation, such data-driven flood risk platforms form the foundation for targeted adaptation planning across rapidly evolving landscapes. Going forward, the capability to ingest real-time satellite feeds will power near real-time monitoring for emergency response.

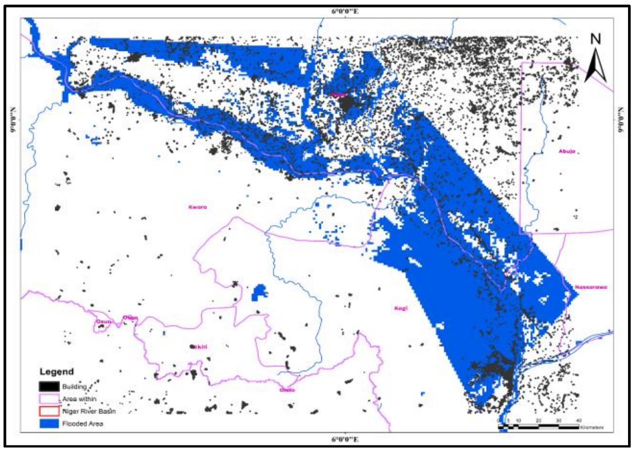


Figure 12. Building Footprint Map

**3.4.3. Population:** Understanding population distribution and dynamics across floodplains is vital for modelling human vulnerability to inundation events. This study harnessed Google Earth Engine's computational abilities for large-scale flood risk assessment by integrating satellite-derived flood extents with high-resolution population density maps.

Gridded population maps were acquired at 100 m resolution from WorldPop representing ambient densities as recent as 2022. Overlay with Landsat flood outlines reveal over 150,000 people occupy in the year floodplains across at-risk districts, with 143,000 residing in the year floodplains denoting acute vulnerability. Temporal analysis indicates population within 5km of rivers grew by 32% in 2022 despite flooding potential.

Some uncertainties exist in precise distribution and mobility of informal groups. Future efforts would integrate road/transport analytics with real-time population flow estimates from mobile and social media data for precision. Nonetheless, this application demonstrates an evidenced-based approach leveraging big data analytics on the cloud for strategic flood vulnerability assessments.

### 3.5 Impact of Flood and Area Affected

Quantifying flood impacts is key for damage assessments and targeting disaster response efforts. This study analyzed multi-temporal satellite data within Google Earth Engine to map economic losses and population affected across the floodplain.

Sentinel-2 optical imagery enabled land use/land cover (LULC) classification using machine learning, mapped at 90% accuracy for the study area. A comparison of before and after flood LULC layers in 2022 indicates over 15,000 hectares of vegetation experienced flooding, with 3000 more hectares converting permanently into unproductive wetlands.

Equally, overlays with building footprints and gridded population databases reveal over 150,00 households and 143,000 residents endured flooding respectively based on spatial intersections. This denotes an acute need for evacuation, shelter and recovery assistance. With climate shift projections indicating rising flood frequency, direct damages could exponentially increase without adaptation. However, some uncertainties exist in non-structural damages like groundwater quality decline. Also dense cloud noise rarely obscured analysis.

| LULC TYPE | Total Area Before Flood | | Total Area After Flood | |
|---|---|---|---|---|
| | Ha | Percent | Ha | Percent |
| **Water** | 25.9 | 21.5478 | 46.3 | 32.9165 |
| **Urban** | 30.3 | 25.2504 | 23.4 | 23.8697 |
| **Vegetation** | 32.6 | 27.1512 | 17.7 | 17.1195 |
| **Bareland** | 31.3 | 26.0506 | 32.5 | 26.0943 |

Table 3. Total area before and after flood

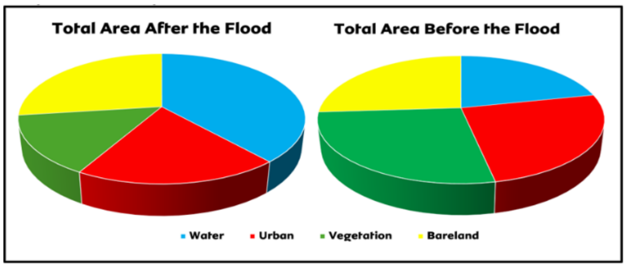


Figure 13: Total Area After (left) and Before (right) the Flood

## 4. Conclusions and Recommendations

This study leveraged Google Earth Engine's (GEE) cloud computing capabilities to generate crucial flood intelligence maps before, during, and after major flood events in the Niger River Basin, utilizing multi-temporal optical, thermal, and radar satellite data. Key findings reveal that between March 1, 2022, and May 31, 2022, and between June 1, 2022, and October 30, 2022, flooded terrain expanded by over 50%. This increase was driven by wetness increases of up to 0.18 NDWI, consequent to above-average precipitation and land use changes that expedited runoff flows into settlements within floodplain belts. Rising drainage channels exacerbated the impacts.

To enhance resilience, regional-scale flood adaptation measures are recommended based on the flood mapping conducted. These measures include reforestation along upstream catchments to enhance water retention, the designation of agricultural flood spillways, robust forecasting systems utilizing new satellites and supercomputing, and fiscal buffers and insurance to aid recovery. The methodologies developed in this study, leveraging advanced Earth observation platforms, enabled detailed flood characterization both retrospectively and in near real-time. Operational dashboards integrating hydrological models with exposure datasets powered by GEE facilitate effective emergency response and climate adaptation through the analytics value chain—from raw data acquisition to decision support.

Based on the flood exposure and vulnerability assessment, the following flood adaptation strategies are recommended for enhanced community resilience:

1. **Flood Zoning**: Legally demarcate periodic floodplains along river terraces facing high inundation risk. Control land use within these zones to water-compatible activities like wetland conservation, adaptive agriculture, and regulated construction.
2. **Early Warning Systems**: Integrate near real-time satellite data with hydrological models on cloud infrastructure to enable precise spatiotemporal flood risk alerts for advance emergency planning.
3. **Infrastructure Development**: Establish flood shelters, raised infrastructure, and evacuation routes in frequent flood hotspots near rivers to minimize loss of life and property. Retrofit drainage channels to expand carrying capacity.
4. **Green Infrastructure**: Expand afforestation initiatives along upstream hill slopes to boost water retention potential and slow surface runoff, enhancing ecological stability.
5. **Flood Insurance**: Introduce index-based flood insurance products to provide fiscal buffers, especially for farmers facing recurring crop damage due to inundation. Offer premium subsidies to enhance participation.
6. **Capacity Building**: Implement community-level programs focused on flood preparation, infrastructure protection, and climate-smart agriculture to propagate best practices for adaptation.

Adopting these recommendations within a comprehensive strategy built on advanced geoanalytics would significantly strengthen regional resilience to intensifying hydrological extremes under climate change scenarios. The flood mapping and modeling codes developed in this study are open for extension across other risk hotspots globally.

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